Computational Enhancement of Accumulated CA-CFAR Process in Side Scan Sonar Data

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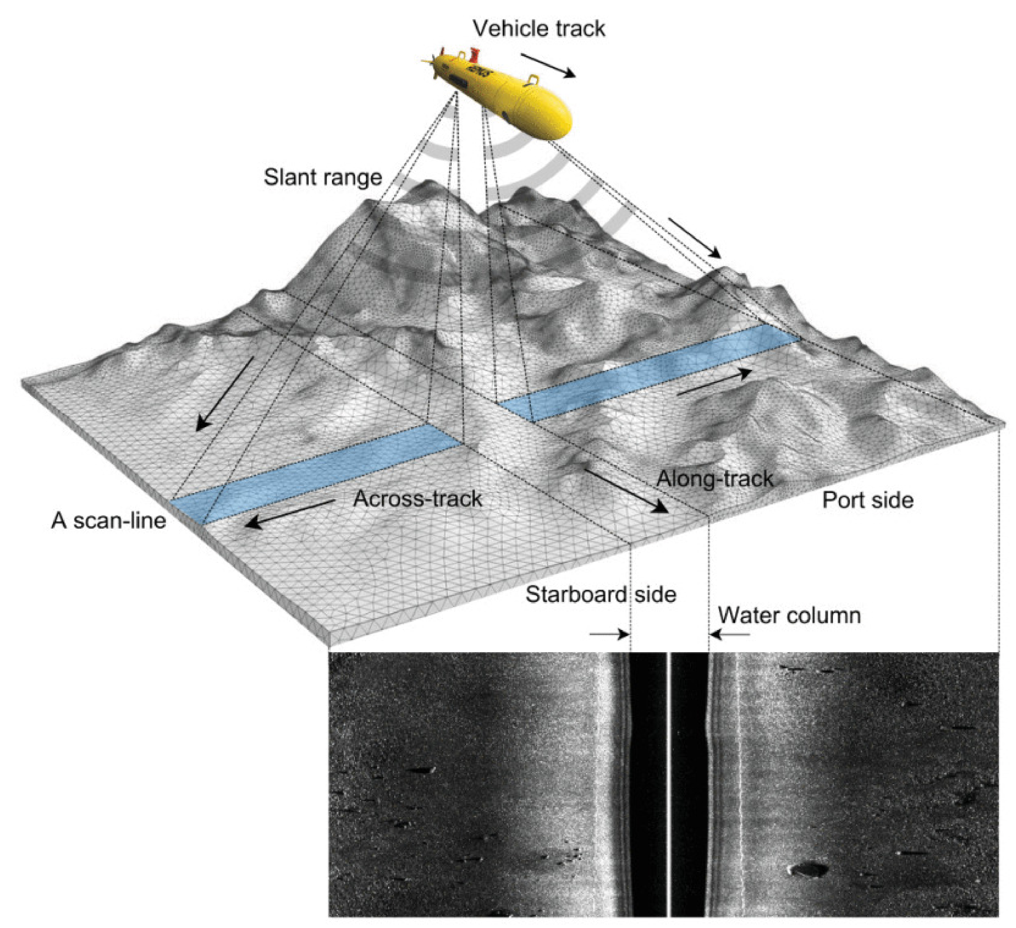
1. SSS: Introduction



- SSS devices (typically 100-500 kHz) generate images with high resolution.
- Uses linear arrays of transducers on the port (left) and starboard (right) sides.
- In each data acquisition cycle, the port and starboard beams extend sideways and downward.
- The nadir and zenith correspond to points of low and high reflection off the surface of the seafloor and the surface of the sea, respectively. The data acquired are projected on a line traced along the seafloor. This scanning line is known as a swath.
- SSS identifies 3 types of regions: acoustical highlight, shadow, and seafloor reverberation.
  - *Highlight:* The area originates from acoustical wave reflection from an object.
  - *Shadow:* Due to a lack of acoustical reverberation behind the object.
  - *Seafloor reverberation:* The remaining areas.
- Segmentation is a computationally intensive process used for the detection and classification of an object from an image.
- SSS data can exhibit significant variations in intensity levels due to factors such as the distance between the sonar transducer and the seafloor, seafloor composition, and the angle of incidence of sound waves. These variations can make it challenging to set consistent intensity thresholds for segmentation.
- Cell Average - Constant False Alarm Rate (CA-CFAR) is a popular method used to estimate adaptive intensity thresholds.

Main References

[1] Gerardo G. Acosta and Sebastián A. Villar *"Accumulated CA–CFAR Process in 2-D for Online Object Detection From Sidescan Sonar Data"* IEEE J. Ocean. Eng., July 2015, 40, 558–569.

[2] D. K. Barton and S. A. Leonov *Radar Technology Encyclopedia.* Reading, MA, USA: Artech House, 1998, pp. 91–93.

[3] G. Huo, Z. Wu, J. Li *"Underwater Object Classification in Sidescan Sonar Images Using Deep Transfer Learning and Semisynthetic Training Data"* IEEE Access 2020, 8, 47407–47418.

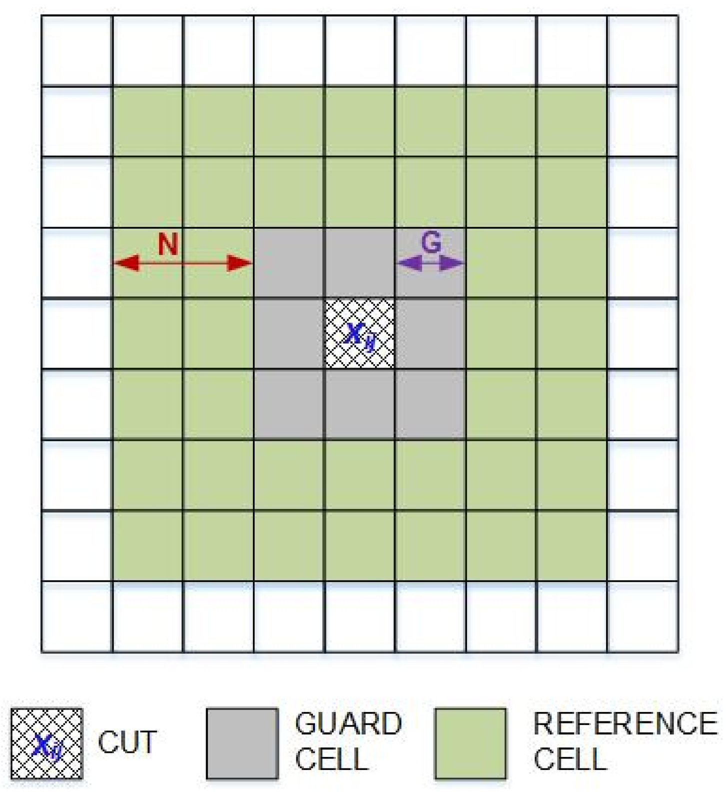
2. CA-CFAR

- CA-CFAR works by setting a threshold for detection that is adjusted based on the local noise and clutter level in order to maintain a constant false alarm rate.
- Threshold estimate $\hat{T}$,

$$\hat{T} = \frac{r}{N_c} \sum_{i=1}^{N_c} x_i,$$

- r denotes the constant multiplier chosen either to attenuate or enhance the detection threshold based on the probability of false alarm (α)

$$r = N_c(\alpha^{-1/N_c} - 1)$$



No. of Reference cells, $\mathbf{N}_c = (2N + 2G + 1)^2$
No. of Guard cells, $\mathbf{G}_c = (2G + 1)^2$
Reference distance, $d_r = N + G$
Guard distance, $d_g = G$

3. Accumulated CA-CFAR

- A typical acoustic image may contain 200-2000 samples, and 2D CA-CFAR computation demands considerable computational resources and time to analyse the entire image.
- Computationally improved 2D CA-CFAR algorithm: Accumulated CA-CFAR (ACA-CFAR) algorithm [1].
- ACA-CFAR reduces the repeated computation by pre-calculating the summations of the reference and guard cells.
- ACA-CFAR algorithm first computes an accumulation matrix, **A**. The $(r, c)^{th}$ element of **A** is calculated as, $a_{r,c} = \sum_{i=1}^{r}\sum_{j=1}^{c} x_{i,j}$
- Sum of the reference cells of CUT,

$$\Sigma_R = a_{r+d_r,c+d_r} - a_{r-(d_r+1),c+d_r} - a_{r+d_r,c-(d_r+1)} + a_{r-(d_r+1),c-(d_r+1)}$$

- Requires only four memory accesses from the pre-computed accumulated matrix.

$N = 2, G = 1, d_r = 3, r = 6, c = 5$

	1	2	3	4	5	6	7	8	9
1	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}
2	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}	x_{26}	x_{27}	x_{28}	x_{29}
3	x_{31}	x_{32}	x_{33}	x_{34}	x_{35}	x_{36}	x_{37}	x_{38}	x_{39}
4	x_{41}	x_{42}	x_{43}	x_{44}	x_{45}	x_{46}	x_{47}	x_{48}	x_{49}
5	x_{51}	x_{52}	x_{53}	x_{54}	x_{55}	x_{56}	x_{57}	x_{58}	x_{59}
6	x_{61}	x_{62}	x_{63}	x_{64}	x_{65}	x_{66}	x_{67}	x_{68}	x_{69}
7	x_{71}	x_{72}	x_{73}	x_{74}	x_{75}	x_{76}	x_{77}	x_{78}	x_{79}
8	x_{81}	x_{82}	x_{83}	x_{84}	x_{85}	x_{86}	x_{87}	x_{88}	x_{89}
9	x_{91}	x_{92}	x_{93}	x_{94}	x_{95}	x_{96}	x_{97}	x_{98}	x_{99}
10	$x_{10,1}$	$x_{10,2}$	$x_{10,3}$	$x_{10,4}$	$x_{10,5}$	$x_{10,6}$	$x_{10,7}$	$x_{10,8}$	$x_{10,9}$
11	$x_{11,1}$	$x_{11,2}$	$x_{11,3}$	$x_{11,4}$	$x_{11,5}$	$x_{11,6}$	$x_{11,7}$	$x_{11,8}$	$x_{11,9}$

$\Sigma_{6,5} = ACC_{2,1} - ACC_{2,8} - ACC_{9,1} + ACC_{9,8}$

4. Proposed Enhancements in ACA-CFAR

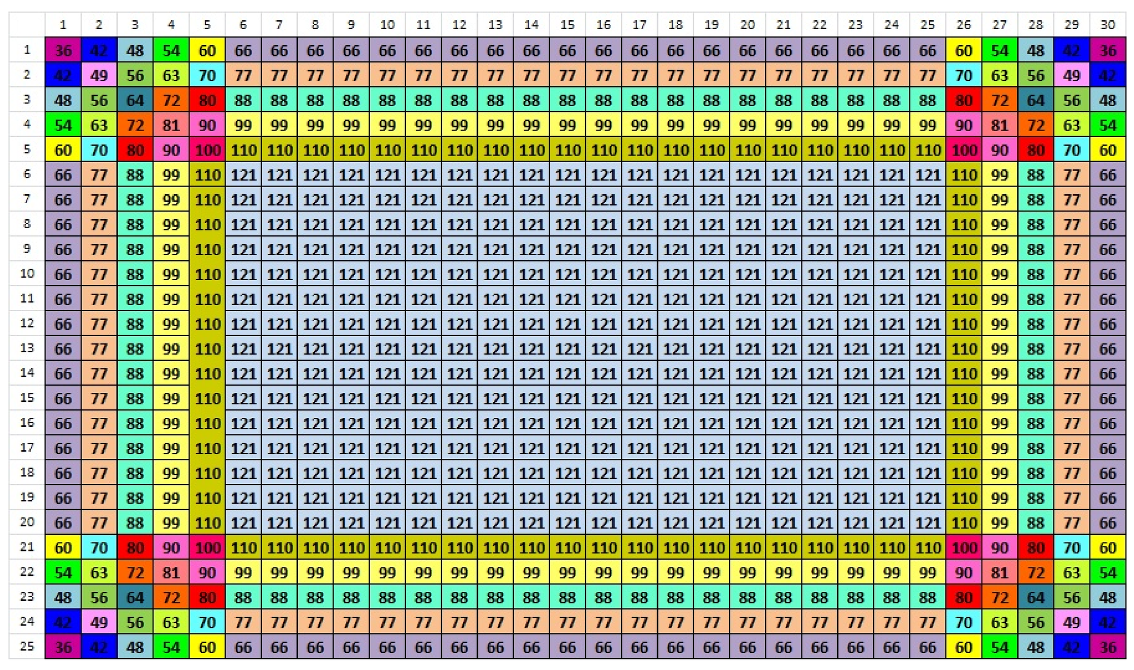
1. **Zero Padding** (**A** matrix generation)

If, $r == 1 \;\&\&\; c == 1$:	$\mathbf{a}(r,c) = x(1,1)$;	✖
If, $p == 1$:	$\mathbf{a}(r,c) = \mathbf{a}(r,c-1) + x(r,c)$;	✖
If, $q == 1$:	$\mathbf{a}(r,c) = \mathbf{a}(r-1,c) + x(r,c)$;	✖
General case: $\mathbf{a}(r,c) = \mathbf{a}(r,c-1) + \mathbf{a}(r-1,c) - \mathbf{a}(r-1,c-1) + x(r,c)$;		⬅

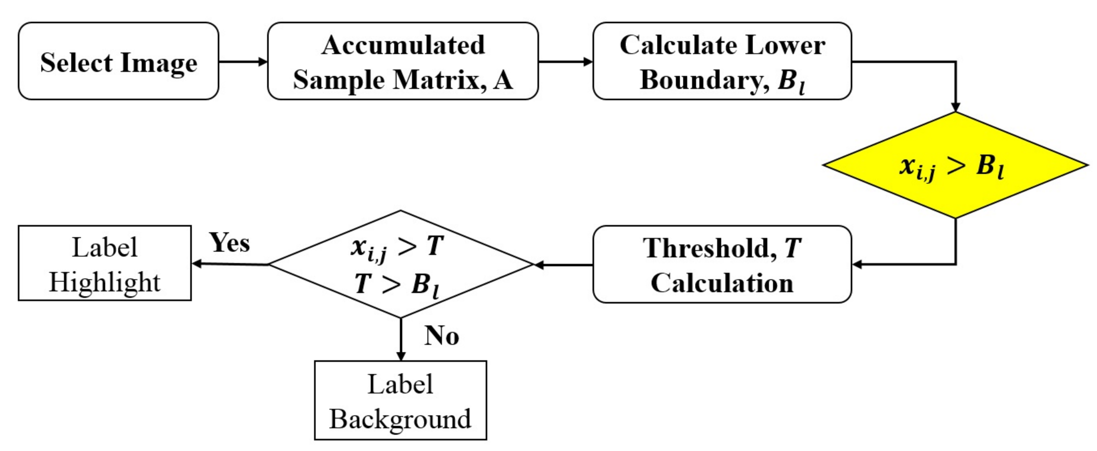
2. **Zero Padding** (Sum of intensity calculation)

General case : $\Sigma_{rc} = \mathbf{a}_{r-(dr+1),\, c-(dr+1)} - \mathbf{a}_{r-(dr+1),\, c+dr} - \mathbf{a}_{r+dr,\, c-(dr+1)} + \mathbf{a}_{r+dr,\, c+dr}$	⬅
If, $r-(d_r+1) \leq 0 \;\&\; c-(d_r+1) \leq 0$: $\Sigma_{rc} = \mathbf{a}_{r+dr,\, c+dr}$	✖
If, $r-(d_r+1) \leq 0$: $\Sigma_{rc} = \mathbf{a}_{r+dr,\, c+dr} - \mathbf{a}_{r+dr,\, c-(dr+1)}$	✖
If, $c-(d_r+1) \leq 0$: $\Sigma_{rc} = \mathbf{a}_{r+dr,\, c+dr} - \mathbf{a}_{r-(dr+1),\, c+dr}$	✖

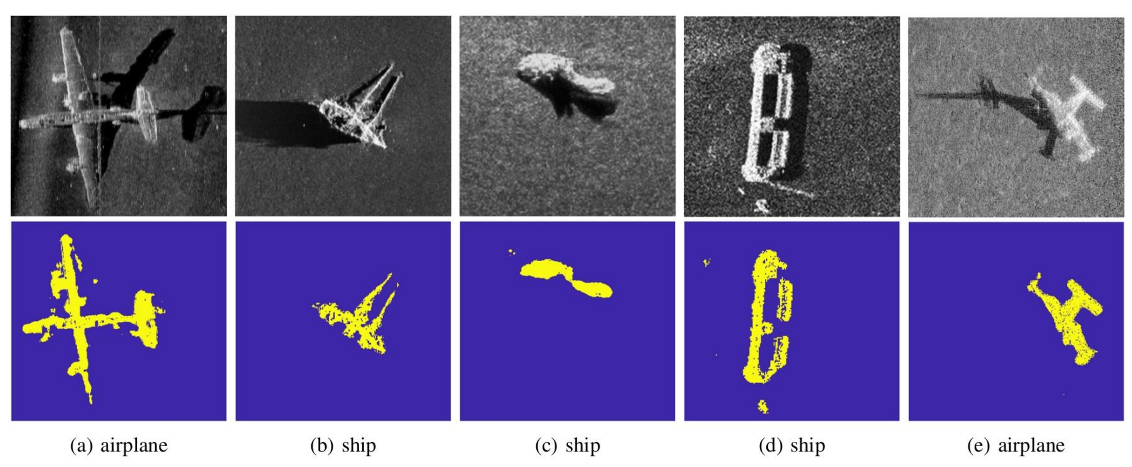
3. **Pre-Computing the** $\mathbf{N}_c$ **matrix**



4. **Branch Optimization**



5. Experimental Results



(a) airplane (b) ship (c) ship (d) ship (e) airplane

Fig.	Performance improvement in %			
	ACA-CFAR with Zero Padding	ACA-CFAR with N_c Matrix	ACA-CFAR with Branch Optimization	Modified ACA-CFAR (Algorithm 2)
a	7.4510	18.5277	50.1214	**62.2269**
b	5.1762	17.3903	53.5297	**60.0680**
c	8.8587	18.5906	52.0281	**63.4931**
d	7.5041	19.9137	58.0055	**63.7565**
e	9.2643	19.9546	43.9394	**57.7761**

6. Conclusion & Research Impact

- Significant improvement (more than 57%) in the computation time over the ACA-CFAR algorithm.
- The proposed algorithm is more attractive and suitable for a real-time SSS system which uses low power devices to realize segmentation algorithms for detection and classification of MLOs which helps to protect large valued assets.