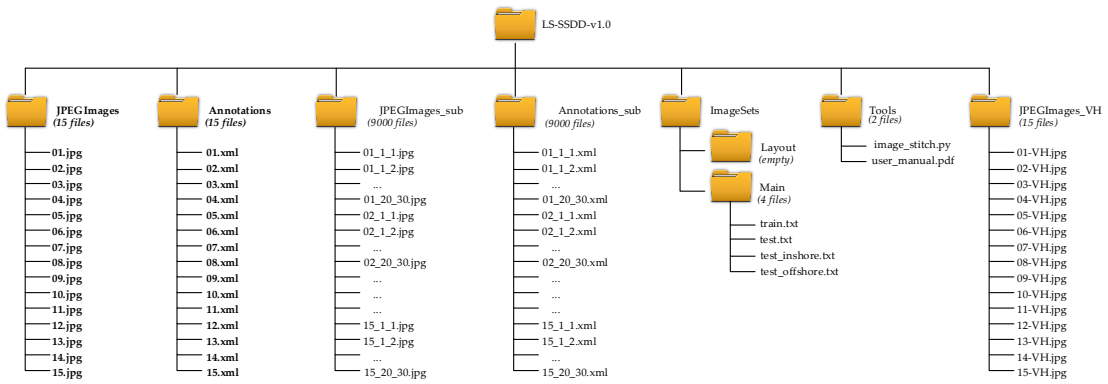
User Manual

----LS-SSDD-v1.0

LS-SSDD-v1.0 is an open Large-Scale SAR Ship Detection Dataset, containing 15 SAR images with 24,000 pixels × 16,000 pixels, from Sentinel-1 satellite.

The file directory of LS-SSDD-v1.0 is as follows.



There are seven file folders in the root directory of *LS-SSDD-v1.0* — (1) **JPEGImages**; (2) **Annotations**, (3) **JPEGImages_sub**; (4) **Annotations_sub**; (5) **ImageSets**; (6) **Tools**; and (7) **JPEGImages_VH**.

JPEGImages has 15 files which contains the 15 raw large-scale space-borne SAR images that are numbered as from 01.jpg to 15.jpg. The size of these SAR images is 24,000×16,000 pixels. **Annotations** has 15 files which contains the 15 ground truth label files of real ships that are numbered as from 01.xml to 15.xml. These labels files are in line with PASCAL VOC standard.

JPEGImages_sub has 9s000 files which contains 9,000 sub-images with 800×800 pixels that are obtained from the raw 15 large-scale SAR images based on image cutting as from 1_1.jpg to 1_30.jpg, from 2_1.jpg to 2_30.jpg, …, and from 20_1.jpg to 20_30.jpg. In addition, these sub-images are numbered as *N*_*R*_*C*.jpg where *N* denotes the serial number of the large-scale image, *R* denotes the row of sub-images and *C* denotes the column. It should be noted that these sub-images are actually used in our network training and test in this paper, due to limitation of GPU memory. If there are some distributed High Performance Computing (HPC) GPU servers, one can direct train the raw 24,000×16,000 pixels large-scale SAR images.

Annotations_sub contains 9,000 label files of ship ground truths numbered as from 1_1.xml to 1_30.xml, from 2_1.xml to 2_30.xml, …, and from 20_1.xml to 20_30.xml, respectively corresponding to 9,000 sub-images with the same file number.

ImageSets contains two file folders (*Layout* and *Main*). *Layout* is used to place ship segmentation labels for future version updates, and *Main* is used to place the training set and test set division files (*train.txt* and *test.txt*). Similar as HRSID that regarded images containing land as inshore samples, we follow this means to divide the test set into a test inshore set and a test offshore set (*test_inshore.txt* and *test_offshore.txt*) to facilitate future studies of other scholars who focus on inshore ship detection, because it is more difficult to detect inshore ships than offshore ships.

Tools contains a Python tool file named as *image_stitch.py* to stitch sub-images' detection results into the original large-scale SAR image. Finally, we also provide a user manual for other scholars' easier use, named as *user_manual.pdf*.

JPEGImages_VH has 15 files which contains the 15 raw large-scale space-borne SAR images with VH cross-polarization numbered as from 01_VH.jpg to 15_VH.jpg, that is used for future dual polarization research. In addition, these 15 VH cross-polarization SAR images possess the same label ground truths as VV co-polarization. In this paper, we only provide the research baselines of the VV co-polarization.

The product IDs are available as follows to link to and obtain additional information about the images by searching the specific product IDs in the website of Copernicus Open Access Hub.

Image ID	**Product ID**
01.jpg	S1B_IW_GRDH_1SDV_20200620T084112_20200620T084137_022115_029F80_B189
02.jpg	S1B_IW_GRDH_1SDV_20200620T165738_20200620T165803_022120_029FAC_17D8
03.jpg	S1B_IW_GRDH_1SDV_20200620T170123_20200620T170148_022120_029FAC_EB9E
04.jpg	S1A_IW_GRDH_1SDV_20200611T021508_20200611T021533_032963_03D175_8263
05.jpg	S1A_IW_GRDH_1SDV_20200621T001544_20200621T001609_033108_03D5E1_330F
06.jpg	S1A_IW_GRDH_1SDV_20200617T061925_20200617T061950_033053_03D42C_FD7D
07.jpg	S1B_IW_GRDH_1SDV_20200621T063116_20200621T063141_022128_029FED_BA3F
08.jpg	S1A_IW_GRDH_1SDV_20200620T214051_20200620T214116_033106_03D5D5_3DBC
09.jpg	S1A_IW_GRDH_1SDV_20200621T182638_20200621T182703_033119_03D62E_7D45
10.jpg	S1B_IW_GRDH_1SDV_20200619T175644_20200619T175709_022106_029F35_D269
11.jpg	S1A_IW_GRDH_1SDV_20200616T100139_20200616T100204_033041_03D3CE_D4B2
12.jpg	S1A_IW_GRDH_1SDV_20200606T111723_20200606T111748_032895_03CF78_2122
13.jpg	S1A_IW_GRDH_1SDV_20200411T230355_20200411T230420_032086_03B552_CAB1
14.jpg	S1A_IW_GRDH_1SDV_20200618T020711_20200618T020736_033065_03D491_EC43
15.jpg	S1A_IW_GRDH_1SDV_20200616T181812_20200616T181837_033046_03D3F4_9027

Detailed dataset description can be found in the following reference [1]. When using LS-SSDD-v1.0, please cite the following references [1-6].

[1] Tianwen Zhang, Xiaoling Zhang, Xiao Ke, Xu Zhan, Jun Shi, Shunjun Wei, Dece Pan, Jianwei Li, Hao Su, Yue Zhou and Durga Kumar. "LS-SSDD-v1.0: A Deep Learning Dataset Dedicated to Small Ship Detection from Large-Scale Sentinel-1 SAR Images," Remote Sensing, 2020.

[2] Zhang, Tianwen, Zhang, Xiaoling, Shi, Jun, & Wei, Shunjun (2020). HyperLi-Net: A hyper-light deep learning network for high-accurate and high-speed ship detection from synthetic aperture radar imagery. ISPRS Journal of Photogrammetry and Remote Sensing, 167, 123-153

[3] Zhang, Tianwen, & Zhang, Xiaoling (2020). ShipDeNet-20: An Only 20 Convolution Layers and <1-MB Lightweight SAR Ship Detector. IEEE Geoscience and Remote Sensing Letters, 1-5, early access.

[4] Zhang, Tianwen, & Zhang, Xiaoling (2019). High-Speed Ship Detection in SAR Images Based on a Grid Convolutional Neural Network. Remote Sensing, 11, 1206.

[5] Zhang, Tianwen, Zhang, Xiaoling, Shi, Jun, & Wei, Shunjun (2019). Depthwise Separable Convolution Neural Network for High-Speed SAR Ship Detection. Remote Sensing, 11, 2483.

[6] Tianwen Zhang, Xiaoling Zhang, Jun Shi, Shunjun Wei, Jianguo Wang, Jianwei Li, Hao Su, and Yue Zhou. Balance Scene Learning Mechanism for Offshore and Inshore Ship Detection in SAR Images. IEEE Geoscience and Remote Sensing Letters, 1-5, possible publication. Or cite the format in arXiv, Tianwen Zhang, Xiaoling Zhang, Jun Shi, Shunjun Wei, Jianguo Wang, Jianwei Li, Hao Su, and Yue Zhou. Balance Scene Learning Mechanism for Offshore and Inshore Ship Detection in SAR Images. arXiv 2020, arXiv:2007.10714.