**I 声呐图像本身存在的问题**

1. 可获得的训练数据与测试数据不匹配，测试机与训练集在统计上分布有差异，易造成过拟合。[1]

众多的应用场景下，需要测试数据依赖于环境，因此会与训练的数据集具有不一致性（no homogeneity）[4]

2. 理想的声呐图像难以获取，多数声呐图像均有不同程度的形变，质量较差[2]

3. 对于声呐图像的interpretation较为困难（例如阴影，噪声以及反射等）

"Acoustic waves can travel great distances on water with small attenuation, depending on frequency, **but interpreting an image produced by a sonar can be challenging**." [5][6]

4. 数据集数量稀少以及获取困难：but the Underwater community in general has not collected large datasets, mostly due to military secrecy and the small size of the field.[14]

5. 目前可能造成声呐图像质量差异的因素：

不同声呐设备的部署 不同的海拔高度 不同的海底环境 不同系统的面积覆盖率 [19]

6. 海底混响 + 海面混响 ：导致声呐图像半点噪声突出，分辨率下降,目标边缘模糊[24]

7. 船体颠簸：声呐图像亮度不均，对比度不高[25]

**II 针对声呐图像的处理方法的弊端**

1. 对于机载数据（on board data）的利用效率不高[1]

...但是为了实现更有效地利用资源，机载数据处理算法的结果为适应决策提供了信息，必须快速。例如，对于在原位的物体进行重新检测，取决于是否有一种检测算法能够在一开始就能快速执行有限的计算能力。

2. 基于非监督学习的方法（Markvo random field）可以不利用训练数据，但是这类方法的前提是前景物往往会伴随阴影出现，当阴影不明显时这一类方法的性能较差。

3. 一般情况下，针对声呐图像设计的“Detection”和“recognition”的训练方式利用的是不同的途径或是不同的阶段，将二者结合能够提升计算的效率，其原因是特征能够被共享且仅适用一次。[3]

4.针对光学图像的，基于彩色图像的方法，难以在声呐图像中产生有用的proposals。[5]

5.多数方法均使用人工设计的特征(engineering features)[5]

6. 大多数识别的操作均使用离线的方法而非在线，限制了AUV的实地探测能力，也限制了AUV的自主能力[5]

7. In previous works [15, 16, 47, 48], target classification algorithms using standard sidescan sonars have mainly been based on the analysis of the targets’ shadows. With high resolution sonars, we note that more information should be exploitable from the target’s highlight.

早先的工作中，针对侧扫声呐图像的目标分类算法的主要基于其对于阴影部分的分析，而在高分辨率的声呐中，我们认为更多的信息应该来自于前景[18]

8. 介绍传统的声呐图像处理方法的文章（donoise + segmentation）[26]

(1)基于CLUSTERING

GLCM

K-means clustering

(2)基于Markov random field(MRF)

FGMM observation field modeling and parameter estimation

Iteration conditions mode(ICM)

(3)基于level set

**具体划分**

**Recognition**

1. template matching [7][8][9]

[9]需要对模板作出定义，指明目标物的形状，并且需要制定相似的度量（metric）

[7]需要对图像作出分割，因此对于输入图像有预先的假设（strong assumptions）

[8]利用了cross-correlation template去匹配chain link corners

2.engineered feature extractor + a trained classifier[10][11]

false positive 较大

3. features based on shadow or highlight[12]

4.useing integral images to build several kinds of maps that can be compared to produce detections[13]理论背景不明晰，且仅能够在合成孔径声呐上执行，未必能应用于前视声呐图像

5.目前绝大多数的声呐图像分类方法都基于预先设定好的类别(class-specific object)，**其泛化性能不强（这种泛化不仅包括不同的目标物之间形态差异的泛化性，也包括不同声呐所产生的图像之间的泛化性）**，但是对于未知类别(class-agnostic)进行识别也具有很大意义，例如可以提升AUV的感知能力。height-feature measurement for the same given object would be very different in these two environments[5]

**Classification**

1.基于template-based features[7][15]，或是segmentation-based features[16][17]，其提取并且利用的特征本质上依赖于海底的环境，会被环境的变化所影响。

2. 基于前景及阴影几何关系的声呐图像分类方法[22]

3. adaboost 分类方法[23]

**Detection**

1. 多数的水雷检测算法基于低分辨率的SSS而非SAS，该算法主要利用目标物前景与背景的模式的特征进行识别(ost of the existing mine detection algorithms, which were originally designed for lower resolution sidescan sonar imagery rather than SAS imagery, simply search for highlight-shadow patterns characteristic of mines [4]–[9].)[20]

主要弊端：

a. 多数算法都假设图片完整且质量较高

b. 其次，许多检测算法并不能充分利用基于几何形状的目标回波和阴影的范围依赖的性质。

c .对数算法都对环境条件有所限制，而并非依靠从不同区域获取的不同数据集；同时，由于实地环境中存在大量的不匹配情况（mismatch），利用预先标注的数据集将会限定目标物的种类

**Segmentation**

1. 基于马尔科夫随机场的离散前景背景分割方法[21]

[1]Williams, David P. "The Mondrian detection algorithm for sonar imagery." IEEE Transactions on Geoscience and Remote Sensing 56.2 (2018): 1091-1102.

[2]D. Cook and D. Brown, “Analysis of phase error effects on stripmap SAS,” IEEE Journal of Oceanic Engineering, vol. 34, no. 3, pp. 250– 261, 2009.

[3]Valdenegro-Toro, Matias. "End-to-end object detection and recognition in forward-looking sonar images with convolutional neural networks." Autonomous Underwater Vehicles (AUV), 2016 IEEE/OES. IEEE, 2016.

[4]Williams, David P., and Elias Fakiris. "Exploiting environmental information for improved underwater target classification in sonar imagery." IEEE Transactions on Geoscience and Remote Sensing 52.10 (2014): 6284-6297.

[5]Valdenegro-Toro, Matias. "Objectness scoring and detection proposals in forward-looking sonar images with convolutional neural networks." IAPR Workshop on Artificial Neural Networks in Pattern Recognition. Springer, Cham, 2016.

[6]Valdenegro-Toro, Matias. "Object recognition in forward-looking sonar images with Convolutional Neural Networks." *OCEANS 2016 MTS/IEEE Monterey*. IEEE, 2016.

[7]V. Myers and J. Fawcett, “A template matching procedure for automatic target recognition in synthetic aperture sonar imagery,” Signal Processing Letters, IEEE, vol. 17, no. 7, pp. 683–686, 2010.

[8] N. Hurtos, N. Palomeras, S. Nagappa, and J. Salvi, “Automatic detection ´ of underwater chain links using a forward-looking sonar,” in OCEANSBergen, 2013 MTS/IEEE. IEEE, 2013, pp. 1–7.

[9]H. Midelfart, J. Groen, and O. Midtgaard, “Template matching methods for object classification in synthetic aperture sonar images,” in Proceedings of the Underwater Acoustic Measurements Conference, no. S S, 2009.

[10] R. Fandos, A. M. Zoubir, and K. Siantidis, “Unified design of a featurebased adac system for mine hunting using synthetic aperture sonar,” Geoscience and Remote Sensing, IEEE Transactions on, vol. 52, no. 5, pp. 2413–2426, 2014

[11] J. Sawas, Y. Petillot, and Y. Pailhas, “Cascade of boosted classifiers for rapid detection of underwater objects,” in ECUA 2010 Istanbul Conference, 2010, pp. 1–8

[12] Y. Petillot, Y. Pailhas, J. Sawas, N. Valeyrie, and J. Bell, “Target recognition in synthetic aperture and high resolution side-scan sonar,” in Proceedings of the European Conference on Underwater Acoustics, ECUA, 2010

[13]D. P. Williams, “Fast target detection in synthetic aperture sonar imagery: A new algorithm and large-scale performance analysis,” IEEE Journal of Oceanic Engineering, vol. 40, no. 1, pp. 71–92, 2015

[14]Valdenegro-Toro, Matias. "Object recognition in forward-looking sonar images with Convolutional Neural Networks." OCEANS 2016 MTS/IEEE Monterey. IEEE, 2016.

[15]H. Midelfart and Ø. Midtgaard, “Robust template matching for object classification,” in Proc. Underwater Acoust. Meas. Conf., 2011

[16]R. Fandos and M. Zoubir, “Optimal feature set for automatic detection and classification of underwater objects in SAS images,” IEEE J. Sel. Topics Signal Process., vol. 5, no. 3, pp. 454–468, Jun. 2011

[17]J. Del Rio Vera, E. Coiras, J. Groen, and B. Evans, “Automatic target recognition in synthetic aperture sonar images based on geometrical feature extraction,” EURASIP J. Adv. Signal Process., vol. 2009, p. 14, Jan. 2009

[18] Pailhas, Yan, Yvan Petillot, and Chris Capus. "High-resolution sonars: What resolution do we need for target recognition?." EURASIP Journal on Advances in Signal Processing 2010 (2010): 42.

[19] Williams, David P., and Alan J. Hunter. "On the relationship between SAS image resolution and target-detection performance." *OCEANS 2015-Genova*. IEEE, 2015.

[20]D. Williams, “Fast target detection in synthetic aperture sonar imagery: A new algorithm and large-scale performance analysis,” IEEE Journal of Oceanic Engineering, vol. 40, no. 1, pp. 71–92, 2015

[21]S. Reed, Y. Petillot, and J. Bell, “An automatic approach to the detection and extraction of mine features in sidescan sonar,” IEEE Journal of Oceanic Engineering, vol. 28, no. 1, pp. 90–105, 2003.

[22]A. Sinai, A. Amar, and G. Gilboa, “Mine-like objects detection inside-scan sonar images using a shadows-highlights geometrical features space,” in OCEANS 2016 MTS/IEEE Monterey, Sept 2016, pp. 1–6

[23]C. Barngrover, R. Kastner, and S. Belongie, “Semisynthetic versus realworld sonar training data for the classification of mine-like objects,” IEEE Journal of Oceanic Engineering, vol. 40, no. 1, pp. 48–56, Jan 2015.

[24]刘伯胜, 雷家煜. 水 声 学 原 理 (第 二 版)[J]. 2010.

[25]滕惠忠, et al. "侧扫声纳图像增强技术." *海洋测绘* 24.2 (2004): 47-49.

[26]Xinyu, Tang, et al. "Methods for Underwater Sonar Image Processing in Objection Detection." *2017 International Conference on Computer Systems, Electronics and Control (ICCSEC)*. IEEE, 2017.