Image characterisation for domain adaptation, with application to marine mammal detection in drone acquired images for environmental studies

Master 2/Ecole d'Ingénieur internship
The interneship is **located at IRISA, Vannes, Brittany** (Campus de Tohannic)

Expected starting: early 2026 (5-6 months)

Keywords: machine learning, deep learning, object detection, domain shift, domain adaptation, aerial imagery, marine mammals, intrinsic dimensions, scarce or unavailable label, experimental and theoretical studies.

Scientific context The context of this internship is motivated by issues raised in environmental studies with data collected by airborne imagery. An illustration of the type of images obtained by our drone is shown in Figure 1. The figure depicts dugongs, and our objective is to automatically localise them using a machine learning–based object detector [6].

Figure 1: An illustration of the type of images obtained by our drone.

The dugong detection, by object detection methods and supervised learning, requires annotated datasets. Indeed, the effectiveness of object detection models is intricately tied to the quantity of annotated data at their disposal. The annotation step is therefore a task of great interest, both in machine learning (ML) and computer vision (CV), but carrying it out manually is tedious and costly in terms of time and human resources.

The challenge intensifies when a second round of image acquisition is performed with a different sensor, with different acquisition parameters, or under different visual conditions. On the one hand, it is not always feasible to directly use the model trained on the first (annotated) dataset on the second (unlabelled) dataset. This is primarily due to differences in the nature of the data, such as variations in lighting conditions, weather patterns, or even in the class of objects present in the images. The mismatch between the two datasets is a well-known problem in machine learning, commonly referred to as domain shift. The model can therefore provide poor or erroneous performances on the new data. On the other hand, a new model can be trained on the second domain, provided that labels for the second domain are acquired. Besides it leads to increased costs and extended timelines for data preparation, there is a loss of valuable information as the knowledge gained from the first domain is not leveraged at all anymore.

As a trade-off, a more efficient approach consists in the use of transfer learning techniques to allow the model to adapt to the second domain, with minimal new annotations. In the field of machine learning, Domain Adaptation (DA) focuses on adapting a model trained on one domain (called source domain) to perform effectively on a different, but related domain (called target domain), where labelled data may be scarce or unavailable. DA plays therefore a crucial role in improving machine learning models, using knowledge learned from one labelled domain (e.g., drone images of a specific geographic area) to be transferred to a different domain or environment (e.g., images of another region or under different environmental conditions). It reduces the need for annotating new data, leveraging existing labelled datasets while minimising the cost of additional labelling campaigns.

In the literature, there are usually 3 main types of strategies investigated, depending on the level at which the adaptation is applied — either at the *data* level, by modifying or augmenting the training dataset; at the *feature* level, by aligning learned representations; or at the *model* level, by fine-tuning or retraining model parameters.

Scientific goals Expanding the training dataset with new data is a common strategy in machine learning for adapting models to new environments. Several studies have explored this approach, demonstrating its effectiveness across various applications, including image processing. Enriching the input dataset to reduce the discrepancy between source and target domains can be done with synthetic data (providing the model with simulated realistic examples from the target data distribution, [7]) or real examples from the target dataset (providing the model with the true variability of the new domain, [4]).

In this work, we will focus on a strategy consisting in augmenting the training set with some (well chosen) images from the target domain. Nevertheless, the choice of the target images to be added to the training set is not straightforward, as it involves not only selecting the most representative samples in the sense of a given metric but also determining the appropriate number of images required to balance domain diversity and model stability.

In an object detection context with covariate shift between domains, an early study has empirically demonstrated a relationship between model performance and the intrinsic dimension of the two datasets, considering the YOLOv8 architecture. In particular, this exploratory work reported that the complexity of the data manifold, that is the number of independent factors required to describe the data, can strongly influence how effectively a model can be adapted to new data [2]. Moreover, the difference in terms of intrinsic dimension between source and target dataset is related to the regret [3], a measure of how much performance is lost due to the domain shift.

The aim of this project is to evaluate the intrinsic dimension of the images, characterising their underlying structure and/or visual features, as a quantitative measure of the potential gain/lost for model adaptation to the new domain. By understanding and linking these intrinsic properties to generalisation performances [2, 1, 5], the model can be adapted to new datasets with minimal additional annotation effort.

Application to environmental survey Numerical experiments will be conducted on drone acquired images gathered via the monitoring and study of marine mega fauna, more precisely dugongs, by automatic characterisation as a parallel task of the SMART-WING[1] project.

[1] ANR JCJC project, lead by Laura MANNOCCI (CR, IRD, Montpellier): A smart wing for the automated and low-cost aerial monitoring of marine megafauna - `https://anr.fr/Project-ANR-24-CE04-0881`

Expected work In order to address the aforementioned objectives, the work program would be:

- Bibliographical review of the field of domain adaptation in machine learning, with a focus on semi-supervised domain adaptation (SSDA) with few labelled target data, more specifically in the context of object detection
- Bibliographical review of the characterisation of data dimension, more specifically in the context of image data
- Implementation and evaluation of the proposed approach through numerical experiments will be done using two aerial image datasets derived from the work of [8]. Domain adaptation will be characterised for the New Caledonia (S1) and Papua region (S2) datasets. Detection will be performed by alternating the source and target domains. Various mixing strategies will be tested to observe their correlation with the intrinsic dimension.
- Novel image selection strategies will then be proposed.
- Dissemination: Master thesis, and if possible scientific publication (with source codes).

Supervision The interneship is **located at IRISA, Vannes** (Campus de Tohannic), and will be supervised by:

- Gérard Subsol (CNRS / LIRMM-ICAR - gerard.subsol@lirmm.fr)
- Marc Chaumont (UBS / IRISA-OBELIX - marc.chaumont@irisa.fr)
- Chloé Friguet (UBS / IRISA-OBELIX - chloe.friguet@irisa.fr)
- Laura Mannocci (IRD / MARBEC - laura.mannocci@ird.fr)
- Caroline Roffi (Ph.D. Student IRD / MARBEC)

Candidate profile Student in computer science and/or machine learning and/or signal & image processing and/or applied statistics, with good programming skills in Python (Pytorch knowledge appreciated), knowledge of deep-learning for image analysis, and high interest to investigate machine learning methods.

Application Send your CV + Motivation letter + Internship dates / duration + Master transcripts to `chloe.friguet@irisa.fr` and `marc.chaumont@irisa.fr`. Potential candidates will be contacted for an interview. Feel free to contact us for any questions.

References

[1] Rony Abecidan, Vincent Itier, Jérémie Boulanger, Patrick Bas, and Tomáš Pevný. Leveraging Data Geometry to Mitigate CSM in Steganalysis. In *IEEE International Workshop on Information Forensics and Security (WIFS 2023)*, Nuremberg, Germany, December 2023.

[2] Cyril Barrelet. *Approches d'apprentissage automatique pour la détection et la classification des déchets dans les vidéos sous-marines en vue du nettoyage robotisé des fonds marins.* PhD thesis, 2025. Supervision : Goutterfarde, Marc and Chaumont, Marc - SYAM - Systèmes Automatiques et Micro-Électroniques, Université de Montpellier (2022-2025).

[3] Quentin Giboulot, Rémi Cogranne, Dirk Borghys, and Patrick Bas. Effects and Solutions of Cover-Source Mismatch in Image Steganalysis. *Signal Processing: Image Communication*, August 2020.

[4] Wooseok Ha and Yuansi Chen. When few labeled target data suffice: a theory of semi-supervised domain adaptation via fine-tuning from multiple adaptive starts, 2025.

[5] Antoine Mallet, Rémi Cogranne, and Patrick Bas. Linking Intrinsic Difficulty and Regret to Properties of Multivariate Gaussians in Image Steganalysis. In *Proceedings of the 2024 ACM Workshop on Information Hiding and Multimedia Security (IHMMSec '24)*, Baiona, Spain, June 2024. ACM.

[6] L. Mannocci, S. Villon, M. Chaumont, N. Guellati, N. Mouquet, Corina Iovan, Laurent Vigliola, and D. Mouillot. Leveraging social media and deep learning to detect rare megafauna in video surveys. *Conservation Biology*, 36:e13798[11], 2022.

[7] Poojan Oza, Vishwanath A. Sindagi, Vibashan VS, and Vishal M. Patel. Unsupervised domain adaptation of object detectors: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 46(6):4018–4040, 2024.

[8] Caroline Roffi. Evaluating the geographic transferability of deep learning models: The case of dugong detection in aerial images. Master Internship thesis, defense: Rennes, sept. 2025, 2025.