Recent Advances in Visual Sensing and Machine Learning Techniques for in-situ Plankton-taxa Classification

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Abstract

The assessment of planktonic organisms is a prevailing task in marine ecology and oceanography as planktons form the principal food source for consumers at higher trophic levels. Reliable estimates on the production at the lowermost trophic levels are thus an integral part for the management of marine ecosystems. Traditional plankton sampling and analysis are limited in their spatial and temporal context of the organisms' environment, which are often critical clues to a biologist for its habitation. In addition, ship-based sampling as described leads to a high level of uncertainty in the estimation, since point measurements that are intermittent in space and time are used (Reid et al 2003; Lermusiaux 2006; Vannier 2018). A disruptive change in approach to tackle this problem is currently taking place, enabled by the use of autonomous robots (Henthorn et al 2006) and augmented by visual sensing for real-time analysis (Ohman et al 2019; AILARON 2019). Approaches providing taxonomy estimates from time-series image analysis (Sosik and Olson 2008) or via computer simulations (Roberts and Jaffe 2007), with the recent advances in deep learning, enabled by the computational power of multicore CPUs and GPUs, made possible processing and classification of large datasets while learning higher level representations. Enhanced traditional machine learning methods are driven by multiple kernel learning, where general features are combined with robust features and new types from multiple views are defined in order to generate multiple classifiers (Py et al 2016; Dai et al 2016; Lee et al 2016; Moniruzzaman et al 2017). In this paper, we present recent DL methods for microscopic organisms' identification and classification. A proposed DL architecture (cf. figure 2) reported an accuracy of 95% as opposed to (90% - 93% cf. table 2) achieved by the state-of-the-art networks: ZooplanktoNet, VGGNet, AlexNet, ResNet, and GoogleNet, while training over a labeled dataset of extracted objects from images of plankton organisms captured in-situ (cf. table 1). COAPNet is embedded into a light-weight autonomous vehicle (LAUV) for real-time in-situ plankton taxa identification and classification. The LAUV in turn utilizes the feedback from the image analysis to constantly update a probability density map that further enables an adaptive sampling process.

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Introduction

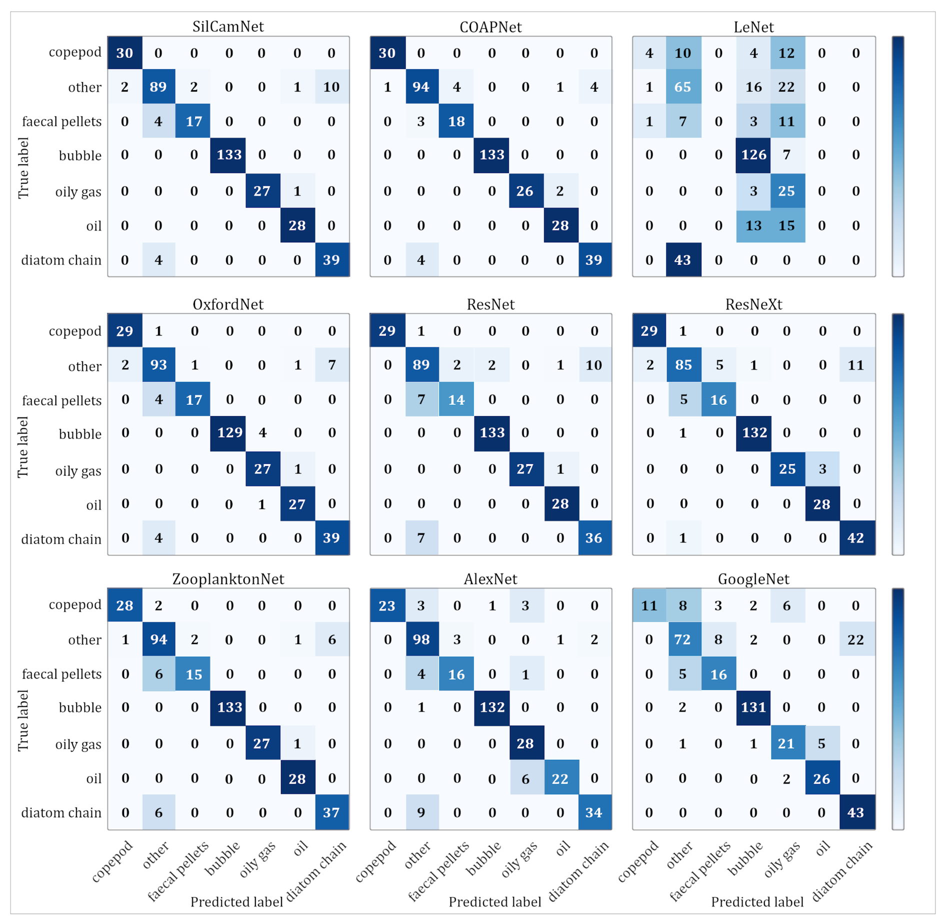
We use autonomous robots (Henthorn et al., 2006) augmented by visual sensing for realtime analysis and assessment of planktonic organizms *(Ohman et al., 2019; AILARON, 2019)*.

We show that approaches providing taxonomy estimates from time-series image analysis *(Sosik and Olson, 2008)* or via computer simulations (Roberts and Jaffe, 2007), with the recent advances in deep learning (DL) made possible the processing and the classification of large datasets while learning higher level representations.

We present how DL methods can be embedded into light-weight autonomous vehicle (LAUV) for real-time in-situ plankton tax identification and classification. The LAUV utilizes the feedback from the image analysis to constantly update a probability density map that further enables an adaptive sampling process.

Performance Comparison

Confusion matrix is a graphical representation that results from training the DNN. Cells on the diagonal represent the True Positive (TP) values of classes recognized by the Network during the training process. Higher TP values, represented by darker colors, indicate better recognition performance.



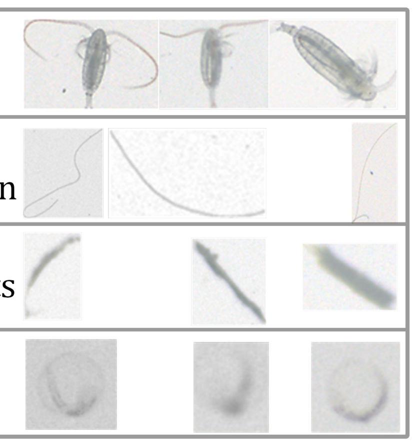
Confusion matrix resulting from training the different DNN architectures over DBI

Datasets

Databases formed from similar imaging environment are developed. This is a necessary step for training the Deep Neural Network (DNN) architecture adopted in the system.

	DBI	DBII	DBIII
Total	7,728	68,792	5,034
bubble	2,636	3,484	824
copepod	657	2,797	857
diatom chain	850	12,399	850
faecal pellets	514	7,211	808
fish egg	–	–	813
oil	671	2,419	–
oily gas	479	483	–
other	1,931	40,013	882

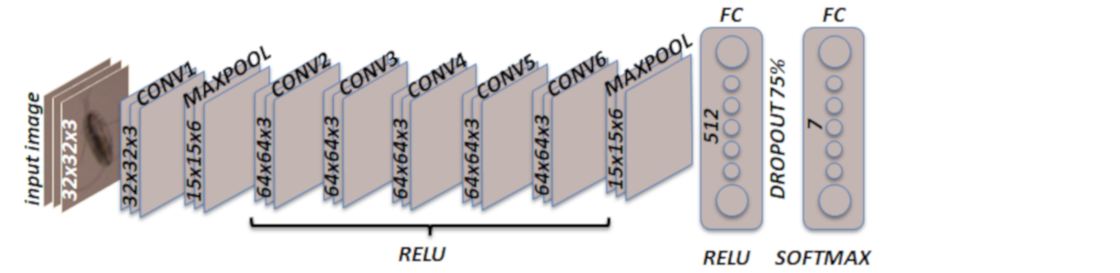
Labeled databases (objects extracted from in-situ captured images), image sizes:1-1190(kB), width: 4-1031(pixels), height:2-811 (pixels).



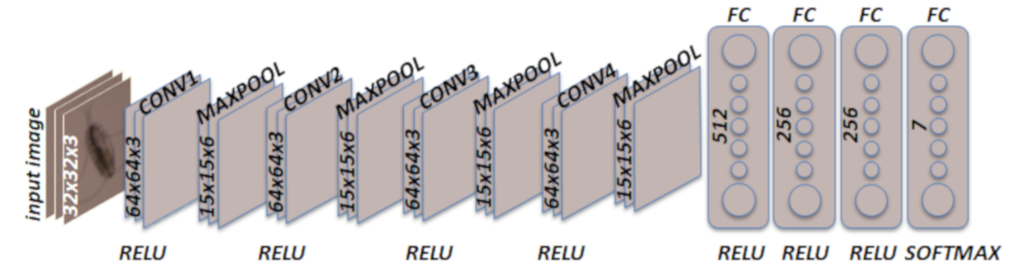
Sample of images from each class.

DNN Architectures

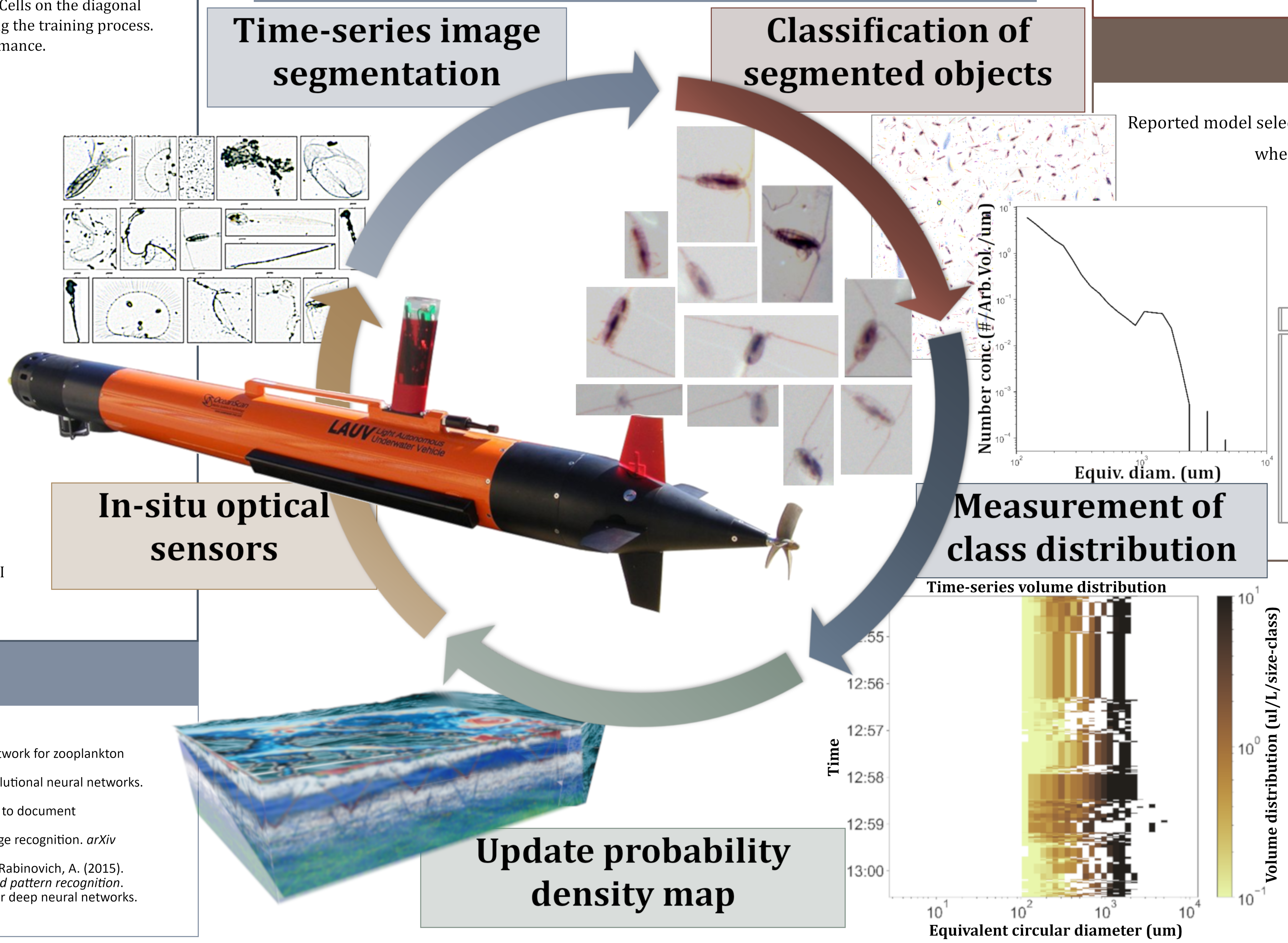
COAPNet is the recommended arhitecture for the in-situ plankton identification and classification task based on the reported performancemetrics over the 3 databases.



SilCamNet: 5 convolutional layers followed by one fully connected layer.



COAPNet: 5 convolutional layers intertwined with max-pooling layers for dimentionality reduction and followed by three fully connected layers.



Performance Metrics

Reported model selection performance metrics are based on training the network over DBI.

where accuracy = $\frac{\sum TP + \sum TN}{\sum Total\ Population}$, precision = $\frac{\sum TP}{\sum TP + \sum FP}$,

recall = $\frac{\sum TP}{\sum TP + \sum FN}$, and F1-score = $2\frac{PR}{P+R}$

TP: the true positive, TN: the true negative,
FP: the false positive, and FN: the false negative.

	Accuracy	Precision	Recall	F1 score
LeNet (LeCun et al., 1998)	59.94%	37.53%	59.94%	45.92%
SilCamNet	93.79%	93.97%	93.79%	93.78%
COAPNet	**95.09%**	**95.16%**	**95.09%**	**95.09%**
OxfordNet (Krizhevshy et al., 2009)	93.28%	93.50%	93.28%	93.31%
AlexNet (Krizhevshy et al., 2012)	91.21%	92.07%	91.21%	91.17%
VGGNet (Simonyan and Zisserman, 2014)	93.54%	93.76%	93.54%	93.44%
ZooplanktonNet (Dai et al., 2016)	93.54%	93.57%	93.54%	93.48%
GoogleNet (Szegedy et al., 2015)	82.68%	84.71%	82.68%	81.96%
ResNet (He et al., 2016)	91.98%	92.03%	91.98%	91.91%
ResNeXt (Xiee et al., 2017)	92.24%	92.63%	92.24%	92.21%

Conclusion

Performance metrics recommend embbeding the COAPNet into the LAUV system. The recommeded architecture is thus adopted and proved to enable in-situ identification and classification of plankton-taxa

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