Computational analysis of spatial species distribution for integrated stationary environmental monitoring

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Fixed underwater observatories (FUO) equipped with different sensors and HD cameras allow a detailed temporal monitoring of smaller areas of interest. Changes in the environment on different temporal scales (e.g. caused by climate change, seasonal fluctuations or sudden events such as oil drilling activities) can now be monitored for selected fauna in the spatial coverage of the image. In order to develop new strategies for spatial monitoring selected key species must initially be investigated under *normal* conditions in an intact environment. Abnormal variations of the investigated natural characteristics, measured with FUOs, may be used as an indicator for changes, potentially of the whole eco-system. In this contribution we investigate the potential of using digital cameras for visual monitoring. We present a first computational approach to study the behavior of shrimp species in a coral reef under *normal* conditions, automatically and by the use of heat-map visualizations. The approach is demonstrated using image data from the long-term observatory LoVe (Lofoten - Vesterålen) between the 1st of May, 2014 and the 18th of June, 2014. The LoVe ocean observatory (http://love.statoil.com) is located 22 km off the Vesterålen coast in northern Norway at a depth of about 260 m. Images were recorded at a time interval of one hour, with a fixed camera orientation, imaging a selected part of a coral reef.

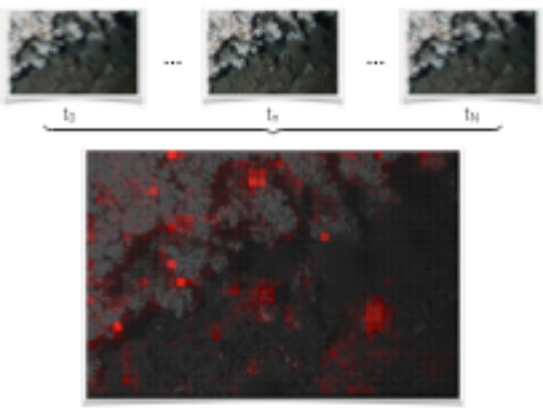

Figure 1*: Instances of the species were automatically detected in the images recorded over time by the observatory. The frequency of the detected species at a position in the images correlates with the intensity of the red color in the heat-map. The average image is used as the background image.*

We can show that instances of the shrimp species can be automatically marked in the image time series. These computationally determined shrimp locations can for instance be used to generate a heat-map overlay for the original image, indicating the occurrences of this species on different positions in the images, i.e. their hot spots over time (Fig. 1).

For algorithmic shrimp detection we employ movement, i.e. local differences to a sliding median image, and color features. These features were evaluated by a machine-learning algorithm, since the detection with standard image processing as we have proposed recently (Purser et al. Biogeosciences, 2014) is not applicable for this data. The generation of a training set for learning algorithm implicates further challenges, as manual annotation is error prone. We can show how pre-segmentation with *super-pixels* can be used to overcome this obstacle. Detection sensitivity is still dependent on local image features, such as e.g. in very dark areas (holes / shadows) lesser or even no shrimp could be detected. While this still limits the significance of the results regarding a comparison of the data from different sites, i.e. from different FUO, the results can of course be used to conduct local studies i.e. compare different behavior in form of heat-maps from different time intervals and it allows therefore measuring the *change* of the behavior of the shrimp species on different time scales. In the oral presentation an overview of the process for detecting the shrimp species is given. Results of the behavior analysis will be presented. Finally the integration of the species detection and the behavior analysis into a real-time environmental monitoring will be discussed.