

Can humans be replaced by computers in taxa recognition?

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Biomonitoring of waterbodies is vital as the number of anthropogenic stressors on aquatic ecosystems keeps growing. However, the continuous decrease in funding makes it impossible to meet monitoring goals or sustain traditional manual sample processing. In this paper, we review what kind of statistical tools can be used to enhance the cost efficiency of biomonitoring: We explore automated identification of freshwater macroinvertebrates which are used as one indicator group in biomonitoring of aquatic ecosystems. We present the first classification results of a new imaging system producing multiple images per specimen. Moreover, these results are compared with the results of human experts. On a data set of 29 taxonomical groups, automated classification produces a higher average accuracy than human experts.

Keywords: Biomonitoring, classification, image analysis, macroinvertebrates.

1 Introduction

Benthic macroinvertebrates are a diverse group of species that quickly react to changes in their environment [15]. Their community composition can reflect even subtle human-induced changes in their environment, making them an ideal indicator group for aquatic biomonitoring [7]. In many countries, biomonitoring of benthic macroinvertebrates is a key part of ecological status assessment of surface waters required by the European Union's Water Framework Directive [17].

The traditional process of macroinvertebrate biomonitoring is the following: First, macroinvertebrates are sampled, usually by using a kick-net method. Second, the specimens are sorted out from the detritus and identified manually

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by an expert. Third, the observed taxa abundancies are used to calculate biological indices indicating changes compared to previous sampling or a reference community. Finally, the index values are combined to evaluate the ecological status of the sampled waterbody.

In macroinvertebrate biomonitoring a large proportion of the total cost and time is spent on manual identification by highly trained experts. It takes several years to train an expert and manually identifying a sample of few thousand individuals can take hours. The monitoring process could be expedited substantially by shifting to automated identification and in recent years there have been many studies on the automated identification of benthic macroinvertebrates [10, 8, 6, 2, 1]. Many biologists tend to oppose the shift to automated identification of macroinvertebrates due to fear of it not being accurate enough. However, manual identification has been found to be surprisingly error prone as well [4]. While there exist studies on the automated classification of macroinvertebrates, to our knowledge, none of them include a comparison between manual and automated identification accuracy.

In this article we introduce a new imaging system producing multiple images per specimen and present classification results on the new multiple image data base. We also compare the accuracy of automated classification to that of human experts.

2 Automated classification

There has been increasing interest in automated classification of benthic macroinvertebrates as continuing budget cuts disable the use of manual identification. In order to use automated classification, the specimens need to be imaged onto a computer and the classification methods need to be trained with data first keyed traditionally by several taxonomic experts. In our analyses, we have used both single image data and multiple image data.

2.1 Single image data

In the first phase of the study, the specimens were scanned onto a computer in single taxon batches using VueScan(c) software (<http://www.hamrick.com/>, Phoenix, Arizona, USA) with an HP Scanjet4850 flatbed scanner at an optical resolution of 2400 d.p.i. The scanned images were normalized to the same intensity range and color balance by using a calibration target. Individual specimens were segmented from the batch image, and each specimen was saved as a single posture image. A set of 64 simple geometry and intensity-based features were extracted for each specimen from the single posture images using

ImageJ [14]. A large data set of 35 taxonomical groups and 6418 specimens was imaged by the Finnish Environment Institute.

There exists a vast amount of different algorithms and models for classification. For the single image data, we compared a group of classification methods and presented a novel Bayesian classifier, RBA, that achieved classification accuracy of 81.2 % [2]. In another work, we used the image data with few modifications: With one taxon excluded from the study and four taxa combined into two, the data comprised of 32 taxonomic classes [1]. In addition to previously explored classifiers, a kernel extension of Extreme Learning Machine [5] was employed and it achieved the highest classification accuracy of 84.1 %.

2.2 Multiple image data

In the second phase of the study, a new imaging system was built to enable multiple images per specimen. The system is described in Figure 1a. It consists of two Basler ACA1920-155UC cameras (frame rate of 150 fps) with Megapixel Macro Lens ($f=75\text{mm}$, $F:3.5\text{-CWD}<535\text{mm}$) and a high power LED light. The cameras are placed at a 90 degree angle to each other to ensure multiple postures of each specimen. The software builds a model of the background and sets off the cameras when a significant change in the view of the camera is detected. A specimen is dropped into a cuvette filled with alcohol. As it sinks, both cameras take multiple shots of it and the resulting images are stored onto a computer (See example images in Figure 1b). The number of images per specimen depends on the size and weight of each specimen: Heavier specimen sink to the bottom of the cuvette faster, leading to a smaller number of images.

Using the described imaging device, the Finnish Environment Institute compiled an image data base of 126 lotic freshwater macroinvertebrate taxa and over 2.6 million images. For the current work, we restricted the number of classes to 29 taxa present at a human proficiency test to compare the classification results with human experts. We also restricted the number of images per specimen to a maximum of 50 images for computational reasons. If a specimen had more images from both cameras combined, we randomly selected 50 of them. The final data comprises of 7742 observations and a total of 367341 images. Using ImageJ, the same set of 64 features was extracted from the images as for the phase one data.

With the 64 features, extracted from the multiple image data, we explored automated classification using MLP, RF and SVM. We split the observations randomly into training (70 %), validation (10 %) and test (20 %) data 10 times. With each data split, we used the training data to build the model and the validation data to select optimal parameter values. Once the parameters were fixed, the training and validation data were combined to train the model

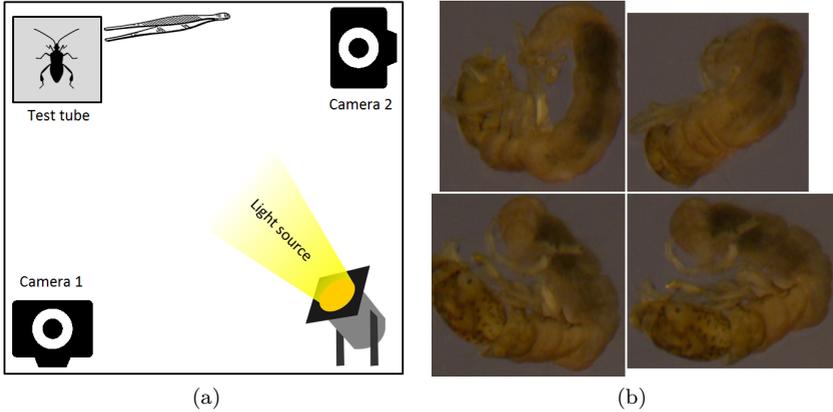


Figure 1: (a): Schematic of the imaging system for macroinvertebrates pictured from above. (b): Example images of a *Polycentropus flavomaculatus* specimen from two cameras. The top row images are from camera 1 and the bottom row images from camera 2.

again. Each image of the test data was classified and the final class for each observation was based on majority vote among all the images of the specimen. All the models were built using R [13]. The results are shown in Table 1.

The highest classification accuracy is achieved with SVM. *Protonemura sp.*, *Hydropsyche saxonica*, *Diura sp.* and *Capnopsis schilleri* have high error rates due to a low number of observations in the training data. The hardest taxa to identify with adequate amount of training data are *Baetis vernus group* which is usually confused with *Baetis rhodani*, and *Kageronia fuscogrisea* and *Polycentropus irroratus* that are confused with several other taxa.

Table 1: Classification accuracy for multiple image data of 29 taxonomic classes. The means and standard deviations are computed over ten splits into training (80 %) and test (20 %) data.

Classifier	\bar{acc}	$sd(acc)$
RF	0.713	0.012
MLP	0.770	0.011
SVM	0.865	0.006

The classification results presented in Table 1 were obtained with very simple features and higher classification accuracy could be obtained using more refined features. In fact, even a simple principal component transformation that makes the features uncorrelated already slightly improves the classification accuracy for SVM ($\overline{acc} = 87.4\%$, $sd(acc) = 0.005$) and MLP ($\overline{acc} = 79.7\%$, $sd(acc) = 0.011$). With a convolutional neural network [CNN, 9] that uses the original images as input instead of features, the classification accuracy is even higher. We applied the MatConvNet [16] implementation of the Alexnet model with batch size 256 and 60 training epochs in Matlab [11] and achieved an average classification accuracy of 93.4 % ($sd(acc) = 0.006$).

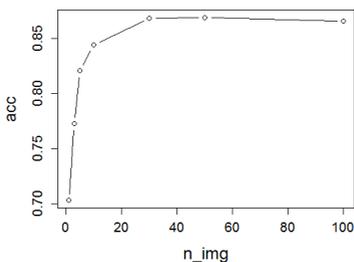


Figure 2: Classification accuracy of SVM plotted against the maximum number of images per specimen.

We also studied, how the maximum number of images per observation affects the classification accuracy with SVM. From Figure 2, it is clear that accuracy increases with the number of images per specimen. However, the difference in accuracy between a maximum of 30, 50 or 100 images is quite small while the difference in computational costs is much greater. It is crucial to consider both when deciding on the number of images to use per specimen. The classification accuracy achieved for the multiple image data presented here is not directly comparable with the results for the single image data of Section 2.1 as the data sets have only 14 taxa in common. However, from Figure 2 it is evident that having more than one image per specimen clearly improves the classification accuracy.

3 Manual classification

In order to compare automated and manual classification, we need classification results on the same set of taxa for both. The Finnish Environment institute

organized a proficiency test on taxonomic identification of boreal freshwater lotic, lentic, profundal and North-Eastern Baltic benthic macroinvertebrates in March 2016. The aim of the test was to assess the reliability of professional and semi-professional identification of macroinvertebrate taxa routinely encountered during North-Eastern Baltic coastal or boreal lake and river monitoring [12]. A part of the proficiency test included 10 experts each identifying 50 specimens of lotic freshwater macroinvertebrates belonging to a total of 46 taxonomic groups, of which 29 are in common with the multiple image data introduced in Section 2.2. The average accuracy for the 46 taxa data was 93.2 % ($sd = 0.061$) and for the 29 taxa in common with the image data, the average accuracy was 92.7 % ($sd = 0.064$). The hardest taxon to be identified was *Hydropsyche saxonica* as half of the specimen were confused with *Hydropsyche angustipennis*.

4 Discussion

The mismatch between funding and biomonitoring goals calls for more efficient monitoring processes. One way to lower the cost of macroinvertebrate biomonitoring is to shift from manual to automated identification of samples. The material costs of the imaging system described in Section 2.2 are approximately 4-5K €, while the price of a high quality stereo microscope traditionally used for macroinvertebrate identification is twice as much. The imaging system is more affordable and it fits well into the work flow of sample processing. Whether using manual or automated identification, the sampled specimens need to be sorted from the detritus. As a natural extension of this, the operator can drop a specimen into the cuvette of the imaging system before placing it into a vial for storing.

Automated classification can enhance the cost-efficiency of the macroinvertebrate sample processing also due to its speed. Training a human expert takes years while – depending on the choice of a classifier and the size of the training data – training a classification model can take 1–5 hours. Predicting taxonomic groups for a sample of 1600 specimens only takes a few minutes of computing compared to the 1–12 hours of manual labor. Also, once a classifier is trained, using it does not require expertise.

Of course, the viability of shifting to automated classification depends on the classification accuracy above all. In this paper, we presented classification results on an image data comprising 29 taxa also present at a human expert proficiency test. The achieved classification accuracy (87.4 % for SVM and 93.4 % for CNN) is in the range of human accuracy of the proficiency test (82.4 – 100%) with the same taxa. The proficiency test included one or two specimen per taxon for each participant while the image test data for automated

classification comprised a total 1557 observations. When using the exact same amount of observations per taxon for testing as in the proficiency test, the classification accuracy for automated classifiers decreases but this is due to the fact that the image data is not a balanced data set and some of the 29 taxa have very few observations for training.

In order to adopt the automated identification process in practice, we need to achieve similarly high classification accuracy with a larger number of taxonomic groups. In this paper, we restricted the taxa to 29 in order to provide a comparison to human experts. Typically, 30–75 macroinvertebrate taxa are encountered at individual sites. While there is need for extending the classifiers to more taxa, the results so far are very promising.

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