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Human and machine factors in algae monitoring performance

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ABSTRACT

We all take our visual systems for granted, and often assume we are always 'near perfect' observers. This is not the case; expert visual recognition is complex and can be error prone. Starting with examples that define the problem I will explore some of the issues of recognition where expert judgements are required.

In addition to 'expert' effects, there are a number of cognitive factors that can severely affect performance, including fatigue, boredom, recency effects, positivity bias and short-term memory effects. Experimental evidence of the impact of these on performance are presented and discussed.

The specimen identifications generated by experts are useful not only to ecology, but to researchers developing systems for automatic labelling of marine plankton. Comparisons of performance are presented, where human experts have been pitted against machines to label plankton. Consensus of opinion is important in reducing errors, yet it is the norm for experts to operate alone. The shortcomings of man and machines engaged in plankton recognition are reviewed and the future of automation is assessed.

1. Introduction

1.1. *Algal monitoring*

Freshwater and marine algae are important flora both ecologically and economically. Some freshwater genera must be monitored as indicators of water quality. Certain species of marine algae are harmful or toxic to humans and must be monitored for health and safety reasons (in the EU: EEC Directive 91/492/EEC), for example, harmful algal blooms in aquaculture. Biodiversity and ecological research necessitates long term time series monitoring of genera and species of algae at various spatial and temporal frequencies.

At present, estimating algal species abundances can only be accomplished through human visual recognition (for example ASTM D4149-82, 1993), DNA analysis (for example Anderson et al., 1999; Bolch, 2001; Penna and Magnani, 1999), HPLC (Claustrea et al., 2004), or in some cases multi-spectral flow-cytometric identification (Dubelaar et al., 2004). Proxies for abundance using Chlorophyll fluorescence are most common (for example Devlin and Lourey, 2000) in routine laboratory assay running alongside microscopy examination.

1.2. *Visual perception*

Humans are endowed with superb visual perception. We learn about our visual world from the moment we are born, and with experience become good at navigating and interacting with the world. Over the twenty or so years it takes to complete a formal education we learn to recognise many classes of objects, natural and man-made. We are also capable of making fine discriminations, for example distinguishing human faces from one another.

It seems that our visual systems are general purpose, although clearly possess properties refined through natural selection and evolution. Even the photograph in Fig. 1 can be recognised by anyone as an underwater scene.

The dictionary definition of an expert is "*having, involving, or demonstrating great skill, dexterity, or knowledge as the result of experience or training*". To be expert at plankton recognition requires training. The task is huge and many plankton experts can only claim expertise in a sub-set of the domain, further constrained by geography. For example, a phytoplanktologist

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Fig. 1 – Two clown fish at home. This aquatic scene is difficult to understand immediately because the upside down bird attached to the bottom of the sea anemone confuses the interpretation. But both fish and bird can be perceived.

may be expert in recognising marine algae, and not fish larvae or copepods, from the North Pacific. With time that expert might extend his or her knowledge to encompass all the algal families, genera and species that frequently occur in the entire Pacific Ocean.

Currently plankton species are grouped into taxonomic classes, following Linnaeus. The categories have undergone some global unification, and synonym databases allow experts to update their knowledge of names where change has occurred. Classification and naming of single celled organisms is experiencing rapid change with the rise in DNA and RNA analysis (Cho et al., 2001; c.f. Consortium of Barcoding of Life http://barcoding.si.edu/). This dynamic state of classification is demanding of experts, as routine identification needs to reflect changes in taxonomic name. Inevitably this can lead to inconsistencies when experts label specimens.

Visual identification of phytoplankton genera is determined from its profile combined with many training examples of surface structure and internal features. Taxonomic descriptions of the features common to a class and those that discriminate between classes are available. The interpretative experience of recognising descriptions of features in actual specimens is essential.

2. Cognitive factors

2.1. Cognitive issues

A number of important cognitive issues affect human performance, including attention and cognitive biases. These can be deleterious to all routine inspection or monitoring tasks, including microscopy for phytoplankton identification. Each factor is reviewed and its impact on expert visual inspection of plankton is assessed.

Humans scan a visual scene by directing eyes in a series of short, fast movements known as saccades (e.g., Duchowski, 2002), which are either reflex actions derived from a stimulus in the field of view (bottom up) or guided by a conscious (or unconscious) desire to search a particular part of the field of view (top–down). So, an entire microscope field of view can be seen through a series of search-based saccades that direct the eyes towards attractors in the scene. Reflex eye movements tend toward colour and high contrast areas of the visual field.

Human vision also has a property called selective attention (Broadbent, 1958). This allows us to tend to objects in particular parts of the visual field to the exclusion of others. It has been likened to a spotlight moving in a darkened room, partially illuminating different areas as it is moved; and is known as the ‘spotlight of attention’ (Treisman, 1982; Crick, 1984). Shifts of attention can be overt or covert (Pashler, 1996).

Pop-out is related to attention, and occurs against a background of distracters (Treisman, 1985, 1986). The item that ‘pops out’ and to which subsequent attention is directed, is variant in some manner from distracters. For example, in a field of horizontal lines a vertical line will pop-out. Fig. 2 demonstrates pop-out for a more complex array of distracters and attractor-oriented plankton. Pop-out can be directed by prior conscious feature selection (i.e., context driven; Reimann et al., 2003), with colour appearing to be the strongest cue.

It is possible, when tallying a cluttered microscope scene, that attentional effects may cause objects to be skipped or enumerated more than once. Conversely, pop-out may ensure certain entities are seen with minimal search effort.

2.2. Biases and performance issues

Performance in identifying and sorting plankton is affected by four cognitive or human factors, (a) a short-term memory limit of 5–9 items, (b) boredom and fatigue, (c) recency effects where a new classification is biased toward the set of most recently used labels, and (d) positivity bias, where specimen identification is biased by prior expectations (Evans, 1987).

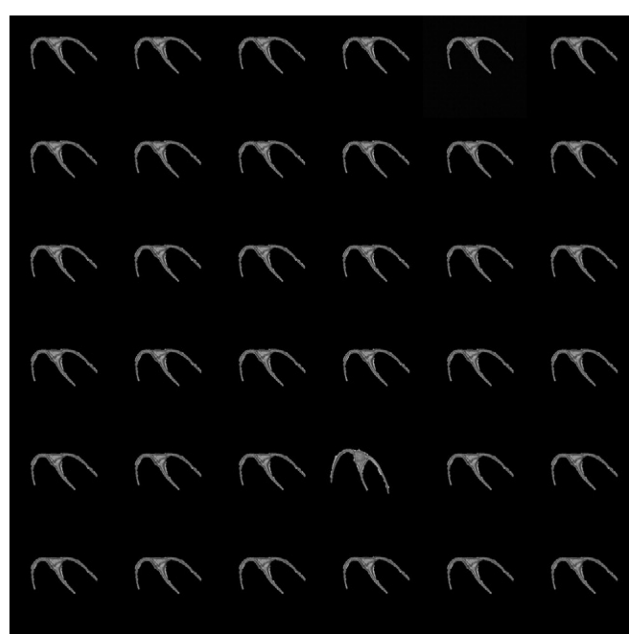

Fig. 2 – Example of pop-out, using *Ceratium arcticum* and *C. longipes*.

Table 1 – A comparison of human and machine performance on microplankton labelling

Categorisation task	Self-consistency within panel individuals	Panel consistency across individuals performance	Machine performance (%)	Reference
Ceratium longipes and *C. arcticum*	Expert: 94–99% 'book' expert 67–83% — 8 experts	95% to 43%	99	Simpson et al. (1991)
5 spp. Tintinnidae	N/A	91% — 6 experts	87	Culverhouse et al. (1994)
3 spp. fish larvae	N/A	N/A	70	Toth and Culverhouse (1999)
5–9 spp. Dinoflagellates	N/A	91–95% — 6 experts	67	Simpson et al. (1993)
23 spp. Dinoflagellates	N/A	83–86% — 6 experts	83	Culverhouse et al. (1996)

Short-term memories can be very volatile. Most people have difficulty remembering even three items after 18 s (Peterson and Peterson, 1959), and Marsh et al. (1997) suggest that short-term memory can decay within 2 s. The nature of working memory also appears biased to favour gain in certain risk-averse decision-making situations (Toth and Lewis, 2002). This bias might affect routine sampling in time-pressured situations and encourage certain memories to be more persistent than others, i.e. fulfilling expectations of species abundances.

Ambient noise, high ambient temperature, difficulty of signal detection, and loss of sleep decrease performance, but rest periods can help (Colquhoun, 1982). Radar operators can have a 70% drop in efficiency within 30 min of commencing a trial, through boredom (Fox, 1971). Many factors affect visual inspection accuracy (Megaw, 1979), including fatigue resulting from overloading the operator and under-loading the operator through boredom or monotony (Welford, 1968). When an operator is overloaded, actions can be confused and judgments may be unclear. By contrast, if the operator is under-loaded attention may drift, signals maybe missed, and performance may be poor.

Recency effects are probably more common in time-pressured inspection or with a fatigued expert. Positivity bias may reduce sample category variance as prior expectations of sample contents define prospects of species frequencies. Both bias effects may lead to incorrect frequency histograms of categories if specimens are binned into the wrong category.

Experts also make up their own rules as they gain experience. A series of experiments by Sokal (1974), using taxonomists, on fictitious animal species revealed idiosyncratic categorisation into species by all participants. Yet, there was a surprising correspondence between participants in the final 'species' clusters across all trials.

3. Expert performance

It is a tacit assumption that trained, expert taxonomists are error-free identifiers, when engaged in identifications of taxa they are expert in. However, the intentional effects, biases and performance issues raised above, together with operational problems (e.g., speed of labelling, length of time performing the task) contribute to errors. Simpson et al. (1991) compared experts for self and mutual consistency and revealed inconsistencies. The task was to label (and not tally) dinoflagellate species in photomicrographs of field collected specimens of *Ceratium longipes* and *C. arcticum*, two closely related species. Taxonomic experts attained 94–99% self-consistency, whereas experienced marine ecologists who were given 'book' descriptions of the two species and a small training set to hone their skills (referred as 'book experts' below), showed 67–83% self-consistency. Overall a mutual consistency measure of 43–95% was obtained for the trial. This suggests that consensus can be difficult to obtain in practice. Yet consensus is the basis of scientific progress.

Further consistency experiments (Simpson et al., 1992, 1993; Culverhouse et al., 1994, 1996; Table 1) show that expert consistency within a panel was never 100%, but varied between 83 and 95% in these experiments. Difficulty is essentially defined by the number of categories the panel was required to consider and keep in mind. It is possible that the short-term memory limit of 5–9 items impacted directly on their performance when asked to label 23 phytoplankton species (Culverhouse et al., 1996). Bias was admitted by one participant, who confessed to mislabelling examples of a particular species for 15 years. The participant only realised the mistake when discussing the labelling task with another participant after the experiment.

A recent study used benthic diatom specimens to compare performance of a trained 'counter' and an 'auditor' in quality-control studies (Kelly, 2001). A range of Trophic Diatom Index counts for 58 UK river samples varied by as much as 30% between expert counters. Thirteen of the 58 counts had more than 10% discrepancy. It appears that the errors are non-linear, with the most error-prone counts being obtained from those samples with the most variety within the sample (i.e. low degrees of species Bray–Curtis similarity as defined in Gauch, 1982).

4. Machine performance

Recently it has become feasible to perform reliable automatic recognition of some groups of marine plankton. A training set of objects is used to establish the prior distributions of features and relate that to specimen name. Machine learning methods are then used to cluster the feature occurrences in test specimens and hence derive a name. Table 2 summarises performance results of current automatic plankton identification systems.

Table 2 – A summary of performance for marine plankton recognition systems

Machine vision system	Grouping criteria achieved	Performance on test data (%)	Summary of features classified	Reference
ADIAC	37 taxa	75–90	Morphological measurements, principal component analysis and a set of pattern classifiers, including neural networks	Du Buf and Bayer (2002)
Zooscan	29 groups	75–85	Forest of classifiers	Grosjean et al. (2004)
SIPPER	5 groups	75–90	SVM categoriser with shape moments (Hu, 1962), granulometric and domain-specific features	Samson et al. (2001), Remsen et al. (2004)
DiCANN	3–23 species	70–87	Low-resolution shape, texture, and size characteristics, which it correlates with object classes through Support Vector Machine	Culverhouse et al. (1996, 2003), Toth and Culverhouse (1999)
VPR	7 groups	72	Morphological shape parameters and texture analysis	Tang et al. (1998), Hu and Davis (2005)
Cytosense	30 groups	91	30 parameters including laser fluorescence and morphological analysis	Dubelaar et al. (2007)

A distinct advantage of automation is the speed of operation. Published data show that CytoSense, Zooscan, SIPPER, and VPR can process many thousands of objects per hour (and, being automata, without fatigue). This is clearly an order of magnitude improvement in identification rate compared to taxonomic experts, though these machines can only perform generic-level discriminations at present.

5. Discussion

All these machines have been tested with field-collected data, either *in situ* or in the laboratory. Machine performance is similar to human expert performance, albeit in small-scale trials. Improvements, in the future, will increase the range and capacity of machine labelling. However, all these machines suffer from a basic problem: they do not work like expert taxonomists or ecologists. This means that they can only operate with data that fits their training set. i.e. through interpolation. Extrapolations from the training set are undefined, although having a training bin labelled 'reject' can help reduce false positive identifications of detritus and species upon which the system has not been trained. Also, new categories cannot always be added automatically. It is important to recognise that a correspondence between machine and human expert results has to be established to ensure that the machines operate with the desired clustering characteristics, such that the number of false positive responses are minimised. For example, rejecting detritus is something humans find trivial, but machine recognition systems find hard.

This set of limitations of machine systems may be because the machines are analysing data signatures that are not unique to species, family or genera, or because the data they are trained on is not error-free. Solow et al. (2001) suggests that training data errors may contribute to noise in a non-linear manner (e.g. 20% error only makes 10% noise in the final result), but there is no evidence to confirm this in plankton recognition systems.

To extend beyond the small-scale it is quite possible that future machines will need to operate with features more consistent with established taxonomic knowledge, since this knowledge structure has been proven to scale well to encompass the diversity seen in the world, and is used by taxonomists to describe differences between species.

Unfortunately taxonomic knowledge is normally presented as visual descriptions of discriminating physical features, such as the presence of apical horns, vacuoles, etc. and relational descriptions such as 'an apical horn is adjacent to a vacuole'. Establishing reliable recognition of what are likely to be variable shapes and textures is complex with current machine vision methods and relational descriptions are not feasible for natural objects where morphological variation between specimens is common. Hence, simpler discriminants are often used in machine vision systems, for example parameter ratios such as width, length, objective measures of texture, Fourier moments and whole-object profile shape descriptions etc. The process can often be reduced to collecting a large number of what are hoped to be orthogonal parameters (perhaps in excess of 40 measurements), training the machine with examples and hoping that many of the parameters provide some level of discrimination for the desired classes. Tests on unseen images reveal the level of success. Poor class separation may be due to insufficient discriminating parameters, insufficient information in the specimen image, too much noise in the data, or overlapping specimens causing two or more objects to be offered as one to the machine analyser. The latter requires overcoming deep machine vision problems before significant progress can be made.

It is acknowledged that expertise takes time to acquire, and is domain specific. Studies into expert performance suggest that the mere number of years experience is only weakly related to performance, but that deliberate practice (i.e. reinforcement learning) is crucial (Ericsson and Lehmann, 1996). The suggestion that experts may become less effective as they get older is therefore theoretically possible. Consider the case of an expert's deliberate practice that includes the idiosyncratic creation of rules (c.f. Sokal's experiments above) having a neutral or even a negative effect on discrimination. This will not improve the expert's skill. Experts working alone are probably more susceptible to this condition, where new rules may be developed and tested without external reference. This is often the norm in laboratories. So how do experts continue to improve when they often are the only local expert in a particular domain? A general solution may be regular inter-calibration within a peer group, aiming to achieve group consensus on routine identification.

6. Conclusions

Expert categorisation of plankton is a skill that builds upon our innate visual abilities. Yet attentional and cognitive-load factors can degrade human performance significantly and may lead to significant errors in routine manual plankton analysis of water samples. Fatigue, boredom, time of day, short-term memory, prior beliefs and biases are some of the important human factors that affect repetitive inspection task performance. These will have measurable impacts on expert performance.

Expert judgements in plankton labelling studies have been reviewed. They reveal that expert performance is not 100%, but can range from less than 60% to 98%. It is clear that experts are not accurate, nor consistent, with the names they give to plankton specimens.

Peer review and inter-expert calibration can help remove human bias. This process is normal for Harmful Algal Bloom monitoring laboratories, where there is a health and safety issue associated with human performance.

Comparisons of human expert versus machine plankton labelling performance have been presented. Of those machines reviewed performance is 70–90% accurate and is approaching expert performance on small-scale tasks.

To improve machine identification to a level that will allow use for identification of algae in bulk water samples, the errors of both man and machine need addressing. Global databases of reference labelled specimen images (and associated multi-spectral data where appropriate) should be prepared and their contents validated. These international reference data sets can then be used for training and testing plankton categorisation systems. They must contain data of specimens that represent the range of morphological and physiological characteristics found in natural habitats (not from cultures). The difficulty in obtaining training data for systems that will operate on a wide range of species/categories cannot be underestimated. It is surely desirable in the future to monitor global distributions of phytoplankton in the same way that conductivity and temperature, at a range of water depths, can be measured (for example Davis, 1991; Hadfield et al., 2007) using the Argo array of 3000 oceanic and coastal floats (c.f The International Argo project: http://www.argo.ucsd.edu/index.html).

Error bars should be quoted on all performance results, for both man and machine. Improvements to machine and human protocols can follow, as errors are systematically identified and removed.

There is a dogma prevalent in marine science that machine recognition systems cannot replace the human. Yet the benefits of adopting automation to assist in algal sample identification are enormous, allowing substantial increases in sample analysis frequency for environmental and health and safety monitoring.

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