Automatic Visual Plankton **Identification**

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Workshop format

- *8:30 Introduction by Convenors*
- **8:35 Cabell Davis (Invited (W5-7254)** – presented by Mark Benfield
- **9:00 Lars Stemmann (W5-7009)**
- **9:15 Elvire Antajan (W5-7192)**
- **9:30 Harry Nelson (W5-7223)**
- **9:45 Catarina Marcolin (W5-7334)**
- 10:00 *Coffee/Tea Brea*k
	- **Posters: Xiaoxia Sun (W5-7149), Karen Manriquez (W5-7186)**
- **10:30 A beginners guide to automatic visual plankton identification**
- **11:30 Open Forum & Discussion**
- 12:30 Workshop ends

A beginners guide to automatic visual plankton identification

Summary

- The 1-D case flow cytometer
- 2D visual features
- Scanners and imagers
- Software
- Operational process
- An example
- Applications
- Machine performance

The 1-D case – flow Cytometry

standard scan profile

Fig.1 Cytosense image in flow examples of two phytoplankton and their accompanying laser fluorescence traces (source: G.Dubelaar Cytosense product flyer, 2006).

Scanning Flowcytometry

Fig. 2 Bottom: ''Nitschia'' type colony of 4 symmetrical cells (photo from: Gerhard Drebes, Marines Phytoplankton, 1974) Top: corresponding CytoSense 1D scan consisting of 5 signal profiles. Circles: scattered light captured at near forward angles; diamonds: scatter at sideward angles; dots: red coloured fluorescence (emitted by the phytoplankton basic pigment chlorophyll a); black line: orange fluorescence (predominantly from accessory pigments); grey line: green/yellow fluorescence (typically by some ciliates and cysts). (source: J. Env. Biol (2004) 6. 946-952). Note the green box encloses the 'signature of one colony individual.

- Non fluorescent particles of $1-3 \mu m$ (sediment-debris). Non fluorescent particles of 3-10 um (sediment-debris). Non fluorescent particles of 10–50 um (sediment-debris). $80-140$ µm organisms with small local (12-18 µm) orange fluorescent section.
- 30-100 µm particles with localized weak to moderate chlorophyll fluorescence.
- Filaments $> 50 \text{ µm}$, cvano type.
- Picoplankton cyano type.

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- ca . 8 μ m cells, moderate accessory pigment.
- 20-35 µm Cryptomonas type cell.
- 50-70 μm Cryptomonas type cell.
- Synura colonies (50-150 µm diam.)
- $ca.$ 7 μ m cells, with accessory pigment fluorescence.
- Picoplankton, green.
- Green cells, 3-15 µm.
- ca. 8 µm cells, high chlorophyll fluorescence.
- Closterium-like, symmetrical cells, 50-80 µm.
- Closterium-like, symmetrical cells, 70-100 µm, very thin.
- Spindle shaped, 70-90 µm cell with double chloroplast $(30-40 \text{ µm})$.
- 19 15-40 µm cells, high chlorophyll fluorescence.
- 20 Dinobryon colonies, 100-200 µm length.

(No taxonomic analyses were available for further identification of these groups.)

Fig.3 (a) distributions of 20 groups of particle in Cytosense analysed water sample, (b) group labels assigned to sample groups (source: J. Env. Biol (2004) 6. 946-952) vertical scale is individuals per ml.

2D analysis – scanners etc.

- Uses digitised images
- Several commercial products (FlowCAM, ZooSCAN, toolsets for microscopy)
- Several free toolsets (Zoo/PhytoImage, ZooProcess, & Weka, Tanagra for statistical analysis

Bespoke Scanners (from Picheral, 2007)

Using a scanner

- Specimens are imaged on a scanner – Can be stained
- ZooImage (shown) & Zooscan automate identification

Zooscan

It is essential to archive the best quality image and the associated metadata plus the scanning parameters.

RAW image: 16 bits Up to 15 x 25 cm Up to 2400 dpi Up to 5000 objects per image

The Zooscan instrument (from Picheral, 2007)

Metadata form

Image feature extraction

• Grey-level equalisation

Zooscan Normalised image (from Picheral, 2007)

Image feature extraction

Normalized image (grey level parametres)

Segmented image (shape & size)

Outlines (shape, size & fractal)

Skeleton area

ZooProcess feature extraction (from Picheral, 2007)

Image (from Picheral 2007) overlaid with bounding box and major/minor axes

Image feature analysis

•Feature sets are extracted for each object

•These can then be analysed for clusters (using multi-dimensional clustering tools such as SVM, Random Forest, LDA)

Plankton Identify (from Picheral, 2007)

An example

CEH.01-07-02.p7+B2.A showing scan of mixed zooplankton (source: Di Mauro, Mar del Plata, AR)

An example

CEH.01-07-02.p7+B2.A showing a small sample of copepods drawn from previous slide

An example

Object detection CEH.01-07-02.p7+B2.A

Fig.12 Morphological data extracted automatically from CEH.01-07-02.p7+B2.A

(in Fig.11).

Training/Testing a classifier

- Expert selects specimens for training set – Identifies 20-50 examples of each class
- Choose classifier
	- Random Forest –fast to train, cannot over learn
	- Support Vector Machine slow to train
	- ANN moderate to train, can over learn
- Train and test cycle
	- Confusion table
	- Calculate recall & precision

Operational use

- Collect specimens, record 'metadata'
- Fix, flush detritus or stain
- Subsample
	- to give ~200 specimens per aliquot
	- Size fractionate
- Scan, extract features, run classifier and record results
	- ESD, and other per specimen measurements
	- Identity (and confidence)
- Export to spreadsheet

Applications More data: These maps are much more appealing...

Data and graphs: X. Irigoien et al, AZTI. Analysis of plankton digital images with PVA, a precursor of Zoolmage

Zooplankton abundance in the Bay of Biscay at two different dates

Note the large number of stations sampled (black dots) and patchiness in the

Fig.13 example analysis using ZooImage (from

www.pices.int/publications/presentations/Zoopl%202007/Zoop%202007%20S9/S9_Grosjean.pdf)

Application examples (cont'd)

Fig..14 Example analysis using ZooImage and FlowCam (from Zarauz et al. 2007).

Application examples (cont'd)

Fig.15 Example Zooscan analysis (from: Picheral 2007a)

(cont'd)

Fig.16 Example Zooscan time series analysis (from: Gorsky et al 2005)

ime evolution of copepods at the different sampling sites determined by the Zooscare
upper figure) and by the Zooscan and manually for the Naples samples (lower figure)

Application examples (cont'd)

S

Evenness (Pielous's J) estimated from Shannon's diversity index on size classes for the series from Villefranche, Naples and Calvi (Zooscan results).

General trends (bold lines) correspond to local polynomial filtering.

Pielous's J: $J: H \cap H \times H'_{\text{max}}$ km δ

Variation coefficient for seasonal size diversity. Data: 403 size spectra obtained using the Zooscan from weekly sampling in Villefranche were transformed into 108 monthly spectra by the Jackknife method.

Fig.17 Further examples of Zooscan time series analysis (from: Gorsky et al 2005)

Zooimage run through

Data set example

Roxana di Mauro, INIDIEP, Mar del Plata, Argentina.

- Sample EH0606 was taken from waters off the Buenos Aires province in 2006 using a 200um net.
- email:rdimauro@inidep.edu.ar

Machine performance

- *HAB Buoy, 26 species 65-90%*
- *Zooscan, 40 groups (semi-automatic) 75-85%*
- *SIPPER, 5 groups 75-90%*
- *Video Plankton Recorder,>7 groups 72%*
- *Cytosense, 20-100 groups,*
- *All can process many 1,000 objects per hour*

Conclusions for automatic visual plankton identification

- Performance OK for ecology
	- Flow cytometry 60 groups
	- Zooscan semiautomatic >40 groups
	- Zoo/Phyto Image 20-30 groups
- Clutter and detritus can cause problems
- Can make useful tools for ecology
- Semi-automatic
	- Keeps ecologist in the loop
	- Reduces false positive/negative rates

Open Forum & Discussion

So how about sorting manually?

HAB buoy images: Rià Arousa, N. Spain June 2005 **Microplankton** (composite)

70 micron

Its hard

Human factors

Human performance in identifying and sorting organisms is affected by several psychological factors:

- (a) Human short-term memory limit of five to nine items,
- (b) Fatigue and boredom: severe loss of categorisation performance (> 50% error!!)
- (c) Recency effects where a new classification is biased toward those in the set of most recently labels and
- (d) Positivity bias, where specimen identification is biased by one's expectations of the species likely to be present in the sample.

Context and other prior cues to category speed recognition significantly.

Human Performance

Ocean Weather Station India 1975

- \checkmark SCOR WG130 experiment
- Zooplankton identification \checkmark by human analyst and by Zooscan machine

Original data Bob Williams from OWS India May 1975 $\sqrt{0.500m}$ LHPR trawl $\sqrt{22}$ net samples $\sqrt{6}$ for humans & machine comparison

Source: SCOR WG130: Automatic Plankton Identification

WS India categories

- Fixed samples in inspection trays
- Mixture of taxa and genera
- Discrimination
	- Some easy
	- Some hard

OWS India: Analyst tally count plot

21 experienced analysts over 700 specimens, in 6 samples

Categories:

- 1. Appendicularia
- 2. Chaetognatha
- *3. Calanus finmarchicus*
- *4. Euchaeta norvegica*
- *5. Metridia lucens*
- 6. Oithona spp.
- 7. Copepoda: small
- 8. Euphausiacea: Adults + furcilia
- 9. Euphausiacea: **Calyptopis**
- 10. Ostracoda

Source: SCOR WG130: Automatic Plankton Identification - unpublished

Human Performance Conclusions

– People are not perfect identification machines

- Usually good at tallying (specimen counting) 15 of 21 > 90% repeatable [mean 700 specimens]
- Can be inconsistent at binning (identifying)
	- 13 of 21 > 90% self-consistent
	- Experts are highly self-consistent >0.9 ICC (Intraclass correlation coefficient)
	- Novices are not self-consistent 0.03 0.76 ICC
- Inter-analyst variation is high

Open Forum & Discussion

- Machine performance
	- Throughput > 1,000 specimens per hour
	- false positive/false negatives (confusions)
		- 50% to 95% binning by category
		- 100% tally count
- Human performance
	- Throughput <300 per hour
	- 70-96% self consistency at tally counting
	- Can be poor (<80%) at binning consistency

The Future

- Challenges include
	- Validating training data using scarce human expert resources
	- Widespread Uptake of automation
- Funding research in this area
	- Cross disciplinary
	- Difficult for referees to review
	- Needs more support

Please join the RAPID group

Discuss!

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