Otolith age estimation
by machine learning approaches

Emilie Poisson Caillault[1], Florentin Vanhelst[1], Bastian Charlet[1], Kélig Mahé[2]

[1] LISIC, ULCO EA 4491, Université du Littoral Côte d'Opale, 62228 Calais, France.

[2] Ifremer, Fisheries Laboratory, 62321 Boulogne sur Mer, France

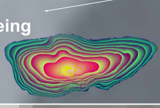
6th International Otolith Symposium
2018,15-20 April
Keelung, Taiwan

Otolith sampling and age estimation by Human experts

- Otoliths are paired calcified structures found in both inner ears of bony fish.
- Otolith are used to determinate fish ages with different growth periodicities ranging from daily to annual increment.
- Between 800,000 and 1,000,000 otoliths are sampled and analysed per year
- Annual cost of approximately $8 million
- The longtest step in this process is the preparation and reading of otoliths by the experts.

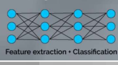
Automation of age reading ?

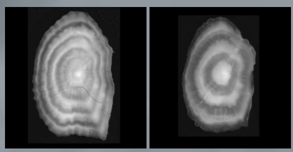
Automated FISh Ageing EU project (AFISA)



Mahé, 2009

Machine learning this study





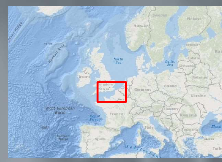
Whole otolith images from plaice

Plaice

Pleuronectes Platessa

8578 sampled Fishes

From surveys and fishing markets
Period: 2010 - 2017
Only Quarters 3 & 4
Age: from 0 to 8+ year classes



English Channel & Southern North Sea

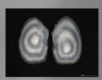
Training dataset : 5713 fishes
Including 20% validation

Test dataset : 2865 fishes

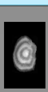
Age estimation by Machine

N=8523

Row images



Preprocessing
Gray transform
Centering



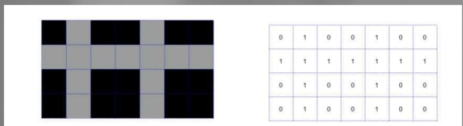
1 Resizing 1

Gray Image
40 pixels*40 pixels

2

Mojette Transform

-> Exact discrete version of Radon transform



Row images

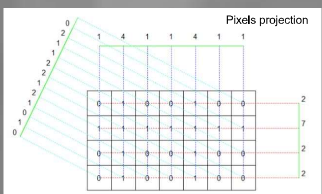
Each projection depends of its angle defined by (p,q) and it consists in a set of bin value M with b the index number of this bin.
All angles are built according to the Farey suite with n order and symmetry
A bin value M is the sum of pixel value f(i,j) according the direction characterized by (p,q).

Katz Criterion to select the number of projection :
sum(p) > P width or sum(q)> Q heigth.

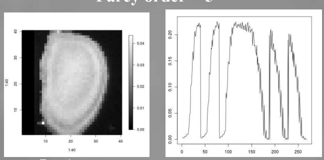
$$M(b,p,q)=\sum_{i=-\infty}^{+\infty}\sum_{j=-\infty}^{+\infty} f(i,j)\times\Delta(b-p\times i+q\times j).$$

-> To reduce the information by recording only few projections that allow to reconstruct original image

Pixels projection



Farey order = 5



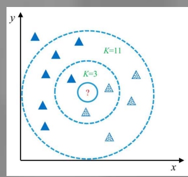
Row image

Projection 13

2

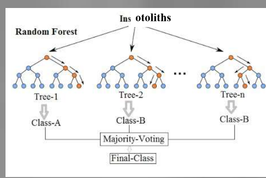
Machine Learning : 3 classifiers

k-NN
k-Nearest Neighbors



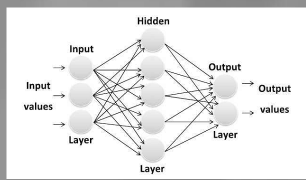
Library class

Random Forest



Library randomForest

MLP
Multi-Layer
Perceptron



Library keras

Results

Human Expert

Age class	Training set	Test set
Age 0	116	49
Age 1	843	406
Age 2	1397	685
Age 3	1468	782
Age 4	1134	523
Age 5	419	237
Age 6	180	92
Age 7	130	54
Age 8+	71	37

Machine Learning

1

- k-nn : k=1/5/10

- Random Forest : mtry=16 ntree=50/100/500

- MLP : linear/1hidden layer 20 neurons/sigmoid function output :softmax activation 9 classes

2

Projections 12,13,15 & 16

30 first Projections

% Agreement

Database	Precision	k-NN 1-nn	5-nn	10-nn	Random Forest RF-50	RF-100	RF-500	MLP Linear-MLP	20-MLP
Training	±0 year	98,5	64,3	57,9	98,4	98,5	98,5	46,1	51,7
Training	±1 year	99,5	88,6	87,1	99,5	99,5	99,5	84,3	87,8
Test	±0 year	42,8	47,3	48,0	51,6	51,3	52,4	42,5	45,7
Test	±1 year	79,6	84,2	85,2	88,7	88,9	89,2	83,0	85,5

Database	Precision	1-nn	5-nn	10-nn	RF-50	RF-100	RF-500	Linear-MLP	20-MLP
Training	±0 year	98,5	61,6	55,7	98,5	98,5	98,5	45,8	43,5
Training	±1 year	99,5	86,1	85,5	99,5	99,5	99,5	82,3	83,8
Test	±0 year	42,8	45,7	45,9	49,6	50,8	51,3	40,6	41,5
Test	±1 year	78,8	82,8	84,4	87,4	87,7	88,2	82,1	83,4

Database	Precision	1-nn	5-nn	10-nn	RF-50	RF-100	RF-500	Linear-MLP	20-MLP
Training	±0 year	98,5	63,5	57,1	98,4	98,5	98,5	-	47,7
Training	±1 year	99,5	88,6	87,3	99,5	99,5	99,5	-	87,4
Test	±0 year	43,7	45,5	47,6	50,7	51,7	51,9	-	44,6
Test	±1 year	81,4	84,3	85,6	88,3	88,6	88,9	-	85,9

30 first projections
Random Forest Classifier
Test dataset : 2865 otoliths

51,9 % of Correct Classification

Predicted age (year) / Observed age (year)

Age group	Age 0	Age 1	Age 2	Age 3	Age 4	Age 5	Age 6	Age 7	Age 8+
Age 0	22	23	4	0	0	0	0	0	0
Age 1	4	303	84	9	6	0	0	0	0
Age 2	2	90	400	159	33	1	0	0	0
Age 3	3	24	169	439	145	2	0	0	0
Age 4	0	7	38	187	277	13	1	0	0
Age 5	0	1	9	33	152	35	2	5	0
Age 6	0	0	1	13	54	10	9	5	0
Age 7	0	1	0	8	29	4	11	1	0
Age 8+	0	0	1	7	16	3	3	7	0

± 0 year ± 1 year

Conclusion & Perspectives

- ✔ Mojette transform results are very close to raw image analysis.
- ✔ k-sensibility in k-nn were correlated with the high intra-class variability and close inter-class size.
- ✔ Database size is not sufficient to build an efficient neuronal network (MLP).
- ✔ Random Forest seemed to be the best classifier according to raw image or Mojette bins.

- The database was built from all otolith images (n=8578) used for stock assessment without prior filtering or images cleaning -> image quality (broken otoliths, dirty otoliths) impacts the results and must be evaluated.
- These results could be improved by optimizing machine learning parameters and by selecting discriminant projections.

Contacts

Emilie Poisson Caillault
LISIC, ULCO EA 4491, Université du Littoral Côte d'Opale, Calais, France
Email: poisson@univ-littoral.fr

Kélig Mahé
Ifremer, Fisheries Laboratory,
Boulogne sur mer, France
Email: kelig.mahe@ifremer.fr

Experiments presented in this study were carried out using the CALCULCO computing platform, supported by SCoSI/ULCO (Service COmmun du Système d'Information de l'Université du Littoral Côte d'Opale).

References

- Mahé, K. (2009), Project no. 044132 Automated FISh Ageing (AFISA): Final Activity 831 Report. http://cordis.europa.eu/documents/documentlibrary/124722831EN6.pdf
- Breiman, L., Ghahramani, Z. (2004). Consistency for a simple model of random forests. Statistical Department, University of California at Berkeley. Technical Report (670).
- https://cran.r-project.org/web/packages/randomForest/index.html
- Guédon, J. (2009), The Mojette transform. Theory and applications. ISTE-WILEY.

Financial Support