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Automated fish age estimation from otolith images using statistical learning

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Abstract

The acquisition of age and growth data is of key importance for fisheries research (assessment, marine ecology issues,...). Consequently, automating this task is of great interest. In this paper, we investigate the use of statistical learning techniques for fish age estimation. The core of this study lies in the definition of relevant image-related features. We rely on the computation of a 1D representation summing up the content of otolith images within a predefined area of interest. Features are then extracted from this non-stationary representation depicting the alternation of seasonal growth rings. Thus, fish age estimation can be viewed as a multi-class classification issue using statistical learning strategies. In particular, a procedure based on demodulation and remodulation of fish growth patterns is used to improve the generalization properties of the trained classifiers. The experimental evaluation is carried out over a dataset of 320 plaice otolith images from age groups 1 to 6. We analyze both the performances of several statistical classifiers, namely SVMs (Support Vector Machines) and neural networks), and the relevance of the proposed image-based feature sets. In addition, the combination of additional biological and shape features to the image-related ones is considered. We reach a rate of correct age estimation of 88% w.r.t. the expert ground truth. This demonstrates the relevance of the proposed approach for the automation of routine aging and for computer-assisted aging.

1 **1 Problem statement and related work**

2 The analysis of fish age-length keys is at the core of stock assessment and ma-
3 rine ecology issues. Acquiring fish age data is mainly performed by interpreting
4 fish otoliths. These calcified structures are formed through an accretionary process,
5 which results in alternated translucent and opaque rings, as illustrated by Fig.1 for a
6 plaice otolith. Fish age is then determined by counting the number of translucent or
7 opaque rings. This tedious task is achieved by expert readers, who typically inter-
8 pret several thousand of otoliths a year. Computer-assisted tools are then sought to
9 help in the acquisition of age-length keys and in the storage of otolith interpretation
10 (Morison et al., 1998; Small and Hirschhorn, 1987; Ogor and Fablet, 2004).

11 [Figure 1 about here.]

12 As far as the automated estimation of fish age and growth is concerned, two broad
13 categories of approach can be distinguished. On the one hand, 1D methods restrict
14 their analysis to an intensity profile extracted along a given reading axis. The issue
15 is then to count and detect its meaningful extrema. Different techniques have been
16 proposed using for instance filtering techniques (Welleman and Storbeck, 1995) or
17 time-frequency analysis (Lagardère and Traodec, 1997). The main drawback lies
18 in the absence of 2D perception of ring continuity, being thus sensitive to local
19 artifacts in otolith images. The evaluation carried out on plaice otolith sets shows

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1 that these 1D approaches achieve only low performance (Guillaud et al., 2002). On
2 the other hand, 2D ring segmentation has also been investigated: deformable tem-
3 plates deduced from the external shape of the otolith (Traodec et al., 2000), a graph
4 framework (Rodin et al., 1996), locally deformable spline-based models (Benzinou
5 et al., 1997) and multi-agent systems (Guillaud et al., 2002). Important improve-
6 ments were obtained for fish age estimation (Guillaud et al., 2002) compared to 1D
7 approaches.

8 [Figure 2 about here.]

9 All these 1D and 2D techniques simply performed age and growth estimation by
10 validating all the detected rings. However, even for rather “easy-to-read” species,
11 such as plaice, the interpretation of fish otoliths remains a complex task. Two main
12 issues arise:

- 13 ● The discrimination of actual growth rings from false rings or checks as illustrated
14 by Fig.2. The presence of false rings is often due to biological or environmental
15 events (sexual maturity, environmental stress,.....). Both ring strength (in terms
16 of image contrast), ring length and inter-ring distances are exploited by expert
17 readers, even if the definition of quantitative criteria is difficult;
- 18 ● the high biological variability both in terms of ring appearance and shape, and
19 of otolith growth, illustrated for plaice otolith growth by Fig.7. This implies that
20 it remains difficult to define objective and quantitative criteria (in terms of ring
21 appearance and in terms of ring growth increments) to discriminate actual growth
22 rings from false rings.

23 These two main difficulties explain that only expert readers with an important ex-
24 perience for a given species and stock can provide reliable age estimate, since they
25 have usually observed several ten thousands of otoliths before being consistent in

1 their otolith interpretation. This difficulty in defining well-formalized criteria for
2 the interpretation of otolith rings has been emphasized by the results of a European
3 workshop on plaice otolith reading held in 2003: inter-reader agreement rates vary
4 from 40% to 95% depending on the readers' experience for fish samples from age
5 groups one to six, whereas this rate is indeed comprised between 85% and 95%
6 for expert readers. These results actually points out the complexity of the otolith
7 interpretation even for "easy-to-read" species.

8 As far as the automation of fish age estimation is concerned, the first consequence is
9 that we are required to go beyond the simple detection of growth rings to carry out
10 the actual interpretation of otoliths from image-based features. Besides, to achieve
11 satisfactory results, it is obvious that one needs to benefit somehow from the experi-
12 ence of expert readers to design a computer-based aging system. Statistical learning
13 approaches are then particularly appealing. They are known to be capable of han-
14 dling complex biological phenomena, and they allow the system to benefit from
15 otolith samples interpreted by expert readers to infer the underlying aging rules.
16 This issue was first considered in (Robertson and Morison, 1998) using neural ap-
17 proaches. Though promising, reported results show that features extracted from
18 otolith images do not bring significant cues compared to biological characteris-
19 tics (fish length, otolith weight, fish sex,...). This contradicts readers' experience,
20 who mainly rely on otolith interpretation for age determination. In fact, biological
21 features are considered only to check possible unrealistic age estimates. Theses re-
22 sults might be due to the use of unadapted image-based features: features formed
23 by the real and imaginary parts of the Fourier coefficients of an intensity profile
24 along a given reading axis were considered (Robertson and Morison, 1998). Such
25 a frequency analysis is generally not suited to deal with otolith images for two
26 main reasons. First, yearly otolith growth is not linear but rather exponential (see

1 Fig.3.a). This results in non-stationary image features in terms of frequency content
2 (i.e., the frequency content of the analyzed signal is “time-dependent”). Second, the
3 otolith is usually thicker around the center. Consequently, image intensities tend to
4 become brighter close to the edge. This leads to the observation of a continuous
5 trend, as illustrated by Fig.3.b. These two important characteristics of otolith image
6 stress that Fourier coefficients should be used as relevant descriptors of the image
7 content.

8 [Figure 3 about here.]

9 In this paper, we also investigate statistical learning for fish aging applications, but
10 with an emphasis on taking into account these two key features of otolith images.
11 We focus on the definition of new image-based features. A semi-local approach is
12 presented in Section 2 to characterize the 2D image content within a given area of
13 interest. Besides, we exploit an *a priori* knowledge on otolith growth to perform
14 an appropriate filtering of the extracted intensity-based representation with a view
15 to enhancing the structures of interest (i.e., image valleys and ridges). We finally
16 present two types of image-based features using either frequency or peak infor-
17 mation. Section 3 outlines the application of neural networks and Support Vector
18 Machines (SVMs) to the considered multi-class classification issue. In particular,
19 a procedure targeted at increasing the generalization properties of the classifiers
20 is presented. The experimental evaluation reported in Section 4 is carried out on
21 a dataset of 320 otolith images. We evaluate the performances of several statisti-
22 cal classifiers and the relevance of the proposed image-based feature sets as well
23 as their combination to biological and geometrical descriptors. Section 5 provides
24 concluding remarks and outlines for future work.

1 2 Image-related features

2 The core of our study consists in extracting relevant features to characterize the
3 content of otolith images, in terms of alternation of translucent and opaque rings.
4 We investigate the use of two different feature sets: frequency-based and peak-
5 based features. The key components of our scheme are a semi-local template-based
6 framework to compute a 1D representation of the 2D image content within a given
7 area of interest, and a growth-adapted filtering to cope with non-stationary features
8 of otolith images.

9 2.1 From the 2D image content to a 1D representation

10 Otolith interpretation is usually performed by experts along a predefined reading
11 axis, as shown by Fig.1 for a plaice otolith. Therefore, the automated analysis of
12 the content of otolith images can be restricted to a region around the main reading
13 axis. Within the considered region of interest, we aim at summing up the associated
14 2D image content to a 1D representation depicting the alternation of the translucent
15 and opaque rings. This more compact representation will ease the extraction of
16 relevant features.

17 [Figure 4 about here.]

To this end, we use a template-based approach inspired from (Traodec et al., 2000)
as illustrated by Fig.4. More precisely, given the otolith center O and an angular
sector \mathcal{S} , the following 1D signal $s_{\mathcal{S}}$ is computed:

$$s_{\mathcal{S}}(\alpha) = \text{med}(I(O + \alpha * T_{\mathcal{S}})) \quad (1)$$

1 where $med()$ is the median operator, $T_{\mathcal{S}}$ is the template model used within \mathcal{S} , I the
2 image intensity function, and α a scaling factor between 0 and 1. As in (Traodec
3 et al., 2000), the template model $T_{\mathcal{S}}$ is given by the sampled external otolith shape
4 within \mathcal{S} . $s_{\mathcal{S}}(\alpha)$ is then the median intensity value along the template $T_{\mathcal{S}}$ scaled by
5 α w.r.t. the otolith center O .

6 Fig.5.b depicts the signal $s_{\mathcal{S}}$ extracted for the otolith image given in Fig.1. Since the
7 scaling of the external otolith shape w.r.t. the otolith center provides locally a good
8 approximation of the shape of the seasonal rings (Traodec et al., 2000), $s_{\mathcal{S}}$ depicts
9 oscillations corresponding to the alternation of translucent and opaque ring. It then
10 provides a representation of the image content within \mathcal{S} , and features describing
11 these oscillations will supply relevant information for fish aging.

12 2.2 *Growth-adapted filtering*

13 As previously stressed, the signal $s_{\mathcal{S}}$ representation involves a frequency modula-
14 tion associated with the non-linear otolith growth. Therefore, a straightforward use
15 of the Fourier transform as in (Robertson and Morison, 1998) is not appropriate. In
16 addition, to extract meaningful image features, noise artifacts as well as the con-
17 tinuous trend of $s_{\mathcal{S}}$ should be removed. Since the relevant frequency content of the
18 signal $s_{\mathcal{S}}$ varies with the distance to the otolith center, we need to locally adapt the
19 scale at which the signal is analyzed to perform this pre-processing step.

As a consequence, we propose a growth-adapted filtering technique. We first per-
form a demodulation step w.r.t. a mean *a priori* growth model. Then, noise arti-
facts and the continuous trend are filtered out using Gaussian filters applied to the
demodulated signal. A growth-adapted filtering is thus introduced to analyze $s_{\mathcal{S}}$.

Given a mean *a priori* growth model $L = \Phi(t)$, with L the distance to the otolith center, and t the time variable in years, s_S is initially demodulated w.r.t. Φ :

$$s_S^{DM}(t) = s_S(\Phi(t)), \quad (2)$$

1 The mean growth model $L = \Phi(t)$ is computed from a sample set of growth pat-
 2 terns estimated on otoliths by an expert. Though non-stationary, the demodulated
 3 signal s_S^{DM} involves a more compact frequency content, what makes easier its anal-
 4 ysis.

To remove the continuous component s_S^T from s_S^{DM} , s_S^T is estimated using a convolution to a Gaussian kernel g_{σ_T} with a large variance σ_T^2 : $s_S^T = g_{\sigma_T} * s_S^{DM}$. High-frequency noise can also be filtered out using a Gaussian kernel with a low variance σ_G , such that the growth-adapted filtering comes to consider the filtered signal s_S^G computed as:

$$s_S^G(t) = g_{\sigma_G} * [s_S^{DM} - s_S^T] \quad (3)$$

5 Fig.5 illustrates the proposed growth-adapted filtering: Fig.5.a depicts the mean
 6 *a priori* growth model used for demodulation purposes, Fig.5.b the signal s_S ex-
 7 tracted for the otolith image given in Fig.1 and Fig.5.c its demodulation version
 8 $s_S^{DM} (-)$, the continuous component $s_S^T (-.)$ and the filtered signal s_S^G . This exam-
 9 ple has been processed with the parameter setting detailed in Section 4. Compared
 10 to the original 1D representation s_S , the filtered version s_S^G provides all useful in-
 11 formation for aging, while making further analysis easier.

12

[Figure 5 about here.]

1 2.3 Frequency-based representation

2 The frequency content of the filtered signal s_S^G might offer a relevant descriptor
3 of the alternation of ridge and valley rings within \mathcal{S} . Rather than computing the
4 Fourier coefficients of s_S^G , we resort to the DCT (Discrete Cosinus Transform) co-
5 efficients of s_S^G . The DCT coefficients are computed as the decomposition of the
6 signal onto a basis formed by cosinus functions. Compared to the Fourier trans-
7 form, it has been proven to lead to more compact representation (Mandyam et al.,
8 1997). Given the DCT coefficients of s_S^G , we consider the N_{DCT} first DCT coeffi-
9 cients to form the feature vector (typically, $N_{DCT} = 200$).

10 2.4 Peak-based representation

11 The analysis of the protocols followed by experts to interpret otoliths leads us to
12 define a second kind of features. More precisely, experts do not rely on the analysis
13 of the image frequency content, but rather on the analysis of the relative positions
14 of the likely translucent and opaque rings. Consequently, we define a new feature
15 vector from the positions of likely growth rings.

Within the angular sector of interest \mathcal{S} , growth rings correspond to extrema of the
signal s_S^G . We first compute the zero-crossings of the first-order derivative of the
signal s_S^G to determine the positions $\{t_1, \dots, t_n\}$ of its local maxima. The proposed
peak-based representation s_S^{PB} is then defined by:

$$s_S^{PB}(t) = \min \{ \rho(t - t_k) \}_{k \in \{1, \dots, n\}} \quad (4)$$

16 where ρ is a distance kernel. In practice, we use $\rho(u) = 2 \tan(\alpha \cdot u) / \pi$, with α
17 a scaling parameter. The resulting signal s_S^{PB} only depends on maxima positions.

1 In particular, compared to s_S^G , s_S^{PB} is invariant to the variability of intensity ranges
2 over images.

3 [Figure 6 about here.]

4 Fig.6 supplies an example of the peak-based representation for the otolith image
5 depicted in Fig.1. If the extracted maxima refer to the actual translucent rings, the
6 proposed peak-based representation can be viewed as a continuous version of the
7 associated growth pattern. The computation of this peak-based representation is
8 also similar in spirit to the computation of signed surface to characterize 2D shapes
9 (Leventon et al., 2000). The vector formed by the values of the signal s_S^{PB} is called
10 hereafter the peak-based feature vector.

11 **3 Statistical learning applied to fish aging**

12 Given the feature vectors extracted from otolith images, fish age estimation is re-
13 garded as a pattern classification issue. Given an otolith image, we indeed aim at
14 mapping the associated feature vector x^n to an age class y^n . To cope with this multi-
15 class classification, we assume that a reference set of labeled examples is provided
16 to achieve statistical learning. We focus on two particular techniques: neural net-
17 works (Bishop, 1995) and SVMs (Scholkopf and Smola, 2002).

18 *3.1 Feature vectors*

19 In addition to the feature types introduced in the previous Section, we might also
20 exploit biological and geometrical features. Our aim will be to evaluate the relative
21 relevance of each feature set w.r.t. the classification task.

1 The biological features are mainly the length, the sex and the catch date. If avail-
2 able, other information such as the sexual maturity or the otolith weight could
3 also be considered. Although these features might be relevant for fish aging is-
4 sues (Robertson and Morison, 1998), growth variability among fish, as illustrated
5 by Fig.7, is usually too high to supply accurate age estimates using only such bio-
6 logical information.

7 Geometrical features computed from the external shape of the otolith might also be
8 considered (M. Cardinale and Mosegaard, 2004). We typically compute the perime-
9 ter, the surface, and the rate between the length along the two principal axis. This
10 type of feature is obviously not sufficient alone to infer fish age. But, we are in-
11 terested in evaluating whether or not it can bring additional cues in combination to
12 other feature types to improve fish age estimation.

13 3.2 *Neural networks*

14 Neural networks have been widely used for pattern recognition issues (Bishop,
15 1995). They are aimed at optimizing the interconnection weights between neu-
16 rons to minimize the mean square error. Here, a back propagation neural network
17 with one hidden layer is chosen. The decision function is a sigmoid. The number
18 of neurons of the hidden layer has been empirically optimized, and set to fifty. In
19 our experiments, we use the Netlab Matlab toolbox (Nabney, 2001).

20 3.3 *SVM*

21 Kernel-based techniques such as SVMs (Scholkopf and Smola, 2002) are among
22 the most efficient approaches for pattern recognition. The key idea of SVMS, which

1 are maximum margin classifiers, is to map the original feature space to a higher
2 dimensional space. The selected mapping Ψ has to verify that the dot product be-
3 tween two points in the new feature space $\Psi(x_1) \cdot \Psi(x_2)$ can be rewritten as a
4 kernel function $K(x_1, x_2)$. The binary SVM classification then resorts to determine
5 the hyperplane separating the two classes within the feature space associated to the
6 kernel function. We let the reader refer to (Scholkopf and Smola, 2002) for further
7 details.

8 In our study, a Gaussian kernel $K(x_1, x_2) = \exp(-(x_1 - x_2)^2 / 2\sigma^2)$ was experimen-
9 tally proven to be the most efficient compared to polynomial and sigmoid kernels.
10 The binary SVM classification is extended to a multi-class classification using a
11 one vs. all strategy. We use the libSVM package (Chang and Lin, 2003) to test
12 for two different SVM techniques: C-SVM and nu-SVM (Chang and Lin, 2003;
13 Scholkopf and Smola, 2002).

14 3.4 Training issues

15 Given a training set \mathcal{T} of otolith images and the associated feature vectors $\{x^k\}_{t \in \mathcal{T}}$
16 (x^k possibly refers to frequency-based, peak-based, biological or shape features,
17 or a combination of these features), we first apply a Principal Component Anal-
18 ysis (PCA) (Bishop, 1995) to the image-related feature vectors to retain the first
19 N_{PCA} components. Statistical learning is then performed within the resulting fea-
20 ture space.

21 To improve the robustness of the learning stage, we virtually increase the number
22 of elements within the training set \mathcal{T} as follows. Thanks to the interpretation pro-
23 vided by the expert, any otolith image k within the training set is associated with

1 a growth pattern $L = \Phi_k(t)$ (i.e., the growth pattern plots the distance from the
2 center to the edge as a function of the age). Using these growth data, we apply
3 a demodulation/remodulation procedure. Given $k \in \mathcal{T}$, the template-based signal
4 s_S^k (cf. Eq.1) is demodulated w.r.t. the growth model $L = \Phi_k(t)$ and remodulated
5 w.r.t. growth models randomly chosen within $\{\Phi_n\}_{n \in \mathcal{T}}$. This scheme generates new
6 virtual signal, which are realistic in terms of growth information.

7 The computation of image-based feature vectors is then applied to the combination
8 of original and virtual signals to create a larger training set. The remodulation is
9 typically performed with five growth models. Thus, the size of the training set is
10 multiplied by a factor six. This is expected to improve the generalization behavior
11 of the trained classifiers.

12 **4 Experiments**

13 *4.1 Training and test sets*

14 [Figure 7 about here.]

15 The experiments are carried out for a database of 320 images of plaice otoliths
16 from age group 1 to 6. The ground truth for fish age estimation is provided by the
17 interpretation of an expert in plaice otolith readings. Due to the lower number of
18 samples in age groups 5 and 6, we merge both groups to end up with a five-class
19 issue: age groups 1 to 4 and 5+. This grouping can also be motivated by the fact that
20 age groups 4 and less usually represent more than 85% of the commercial landings.
21 The age distribution of this otolith set is given in Fig.7.a. As an illustration, Fig.8
22 depicts four sample images for each age group. We also outline with Fig.7.b the

1 biological variability within the processed dataset, which makes difficult the aging
2 issue. More precisely, this plot proves that there is a high overlapping in the distance
3 from the otolith center to the first three translucent rings. This feature makes un-
4 feasible an accurate *a priori* prediction of the ring positions and leads to a complex
5 multi-class classification issue.

6 [Figure 8 about here.]

7 The training set is formed by selecting the two third of the images of each age
8 class, while the remaining images are used for the test set. For each image, image-
9 related features are extracted for five non-overlapping angular sectors of width $\pi/50$
10 around the main reading axis. Angular sectors, for which information required to
11 interpret the otolith is missing due to ring discontinuities or local artifacts, are dis-
12 carded from the training set (in practice, about 20% of the training data were dis-
13 carded), but no such checking is carried out over the test set. We resort to training
14 and test sets including respectively 800 and 600 elements. Using the virtual growth-
15 based signal generation, the training set finally comprises 6000 elements.

16 In the reported experiments, we use the following parameter setting. The growth-
17 adapted filtering is performed with $\sigma_T = 1.5$ and $\sigma_T = 0.05$. For frequency-based
18 representation, we use $N_{DCT} = 200$ DCT coefficients. The peak-based represen-
19 tation is computed with the parameter α of the kernel distance ρ set to 0.1. When
20 applying PCA, we keep $N_{PCA} = 40$ coefficients. Besides, the hyper-parameters of
21 SVMs and neural nets have been set by cross-validation.

1 4.2 Classification results over the test set

2 We evaluate the performances of the proposed approach using different feature sets
3 and classifiers. The performances are analyzed in terms of mean correct classifica-
4 tion rate over the test set w.r.t. the five age groups. The overall evaluation shows
5 that the best results (86%) are obtained by C-SVMs (Scholkopf and Smola, 2002)
6 combined to the peak-based features and the remodulation procedure within the
7 training set. Thus, this configuration is used as the reference in the subsequent.

8 [Figure 9 about here.]

9 We first compare in Fig.9 four statistical classifiers: C-SVMS and nu-SVMs with
10 a Gaussian kernel, neural nets (NN) and linear C-SVMs. These experiments stress
11 the complexity of the considered classification task since linear techniques achieve
12 only poor results. Otherwise, neural nets are also significantly outperformed by the
13 two SVM techniques, while C-SVMs are only slightly better than nu-SVMs.

14 The second evaluation reported in Fig.10 is concerned with the comparison of dif-
15 ferent feature types using C-SVMs: peak-based features (PB), PB features com-
16 bined to the remodulation scheme within the training set (Rem+PB), Frequency-
17 based features combined to the remodulation scheme (Rem+FB), Fourier coeffi-
18 cients of the template-based signal s_S as used in (Robertson and Morison, 1998)
19 (S&R), biological features (B) and geometrical features (G). These results indicate
20 that biological and geometrical features are far too simple to provide alone relevant
21 cues to infer fish age. The influence of the growth-adapted filtering is also demon-
22 strated by the rather low performance (69%) achieved using the frequency features
23 from the template-based signal as in (Robertson and Morison, 1998). Let us stress
24 than in (Robertson and Morison, 1998) frequency features are computed for a 1D

1 intensity profile straightforwardly extracted along the considered reading axis, what
2 should even lower the classification performances given that we use here the pro-
3 posed template-based semi-local scheme. Besides, the peak-based representation is
4 shown to outperform the frequency-based features (86% versus 80%). Finally, the
5 remodulation scheme within the training set actually improves the generalization
6 properties of the trained C-SVM classifier to result in an overall correct classifica-
7 tion of 86% compared to 82.6% without the remodulation step.

8 [Figure 10 about here.]

9 [Figure 11 about here.]

10 The last experiments evaluate the impact of the combination of the peak-based fea-
11 tures to biological and geometrical features. Surprisingly as reported in Fig.11.c,
12 this does not bring any improvement compared to PB features alone. Tab.1 pro-
13 vides the confusion matrix of the classification results for the PB features alone
14 and their combination to the geometrical features. The confusion matrix provides
15 the percentage of samples from any class i assigned to any class j (for instance in
16 Tab.1, 88.3% of the samples from class 1 are assigned to class 1, 10% to class 2,
17 0.8% to class 3 and 0.8% to class 5+). It stresses that this combination tends to de-
18 crease the mean correct classification rate, while the mean-square error is slightly
19 lowered (0.54 for the combination of geometrical and PB features and 0.57 for the
20 PB features alone). This is certainly due to the high overlapping in terms of length
21 and shape features between the different age groups, which decreases the discrimi-
22 nant power of these features.

23 [Table 1 about here.]

1 4.3 *Extension to image classification*

2 From this overall evaluation over the test set, the best configuration is to combine
3 C-SVMs to PB features and to exploit the remodulation procedure. The reported
4 classification results refer to the estimation of fish age from the analysis of one
5 angular sector. Consequently, one can deduce a more robust scheme by combining
6 age estimations for several angular sectors around the main reading axis. Exploiting
7 age estimations for five non-overlapping angular sectors around the main reading
8 axis as detailed previously in the parameter setting, a straightforward voting pro-
9 cedure is used to infer fish age from one otolith image. Tab.2 reports the confusion
10 matrix of the resulting image-based classification. The mean correct classification
11 rate is 88%, and only age group 4 has a classification rate just below 80%.

12 Compared to previous work using statistical learning for fish aging (Robertson and
13 Morison, 1998), the reported classification rates are much greater due to the def-
14 inition of more relevant image-based features. Besides, as reported in (Guillaud
15 et al., 2002), previously proposed 1D and 2D techniques are both outperformed by
16 the proposed statistical learning scheme with respectively 50% and 80% of cor-
17 rect classification. In addition, compared to 2D approaches which require about
18 one minute per image, the SVM classification from PB features just needs a few
19 seconds on a 2.4GHz PC in a Matlab implementation.

20 [Table 2 about here.]

21 Inter-expert agreement rates for plaice otolith readings were recently evaluated be-
22 tween 85% and 95% during the European workshop held in 2003. Thus, our auto-
23 mated scheme shows performances comparable to expert ones, what demonstrates
24 its relevance for an application to routine aging.

1 **5 Discussion and future work**

2 We have dealt with automated fish aging from otolith images using statistical learn-
3 ing. We have in particular defined a new set of image-based features to characterize
4 the alternation of opaque and translucent growth rings within otolith images, and
5 developed a remodulation scheme to improve the generalization properties of the
6 trained classifiers. The evaluation carried out on a dataset of 320 plaice otolith
7 shows that the best performances are obtained using C-SVMs combined to the pro-
8 posed peak-based representation and to the remodulation step before training. With
9 an overall correct classification rate raising 88%, the proposed scheme outperforms
10 previous work and can be favorably compared to inter-expert agreement rates com-
11 prised between 85% and 95%.

12 Considering the proposed scheme as an alternate aging procedure to the acquisi-
13 tion of fish age data by expert readers, different issues arise. First of all, a fully
14 automated scheme requires to combine the technique proposed in this paper to the
15 automation of the acquisition of otolith images and of the detection of the otolith
16 nucleus as proposed in (Cao et al., 2004). For routine aging, the cost-benefits analy-
17 sis of such automated system need to balance between the accuracy reached by the
18 system compared to readers and the gain in terms of processing time. As stressed
19 by our results, for an “easy-to-read” species, such as plaice, the potential gain is
20 huge, since the accuracy levels of the automated system should be in the range of
21 the inter-expert agreement rates, while being greater than those observed for in-
22 training readers. Besides, even if the proposed automated system consider only the
23 younger age groups (up to 6), these age groups represent up to 85% of the sam-
24 pled data for the considered species and stock. More generally, while the number
25 of age groups to be considered needs to be kept rather low to apply statistical learn-

1 ing techniques, the use of the proposed scheme for the most important age groups
2 should at least highly reduced the work to be done by expert readers. Finally, let us
3 stress that in any case the use of statistical learning techniques implies to provide
4 the system with interpreted data. Consequently, expert readers will still be required
5 to interpret at least a representative subset of otoliths to update the trained model
6 and to prevent errors due to important changes over time in ring appearance and in
7 otolith growth patterns.

8 The proposed age estimation technique is not only an alternative to expert readings.
9 It can also be used in a number of different ways to assist the readers for routine
10 aging. For instance, it could provide a low-cost solution for a second reading of
11 otolith samples to evaluate confidence measures of the age estimation. Such mea-
12 sures are of great interest for assessment models (S.A.Reeves, 2003). In addition,
13 the proposed system also provides an automated tool to detect very unlikely age
14 estimates by comparing automatical and reader age estimates. Thus, the readers
15 would be automatically asked for a second reading for unlikely samples. Besides,
16 interactive tools could also be designed for training purposes. These different po-
17 tential applications stress that the proposed system is not limited to the automa-
18 tion of fish age estimation. More importantly, it can provide a series of new tools
19 for computer-assisted aging in the context of quality assurance and quality control
20 (Morison et al., 1998).

21 The application of our approach to other species with more difficult otoliths and
22 longer-lived species needs to be investigated. The proposed system comprised two
23 main steps: the feature extraction step leading to the definition of the peak-based
24 image features, and the interpretation step relying on statistical learning. Let us
25 point out that the proposed approach is generic in the sense that the exploited peak-
26 based representation of the image content within a region of interest can be de-

1 fined from the outputs of any ring detection algorithm (Guillaud et al., 2002; Rodin
2 et al., 1996). As a consequence, for difficult species, for which the proposed lo-
3 cal template-based scheme might not be suited, our future work will focus in de-
4 signing appropriate ring detection techniques. The application of our scheme to
5 longer-lived species might be an issue given the large number of age groups to be
6 considered. A possible solution would be to exploit statistical learning as regression
7 tools rather than classification tools (Scholkopf and Smola, 2002).

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9 The authors wish to thank André Ogor from for his help in the acquisition of image
10 data, and Marie-Line Manten who provides the expert interpretation of the image
11 of plaice otoliths.

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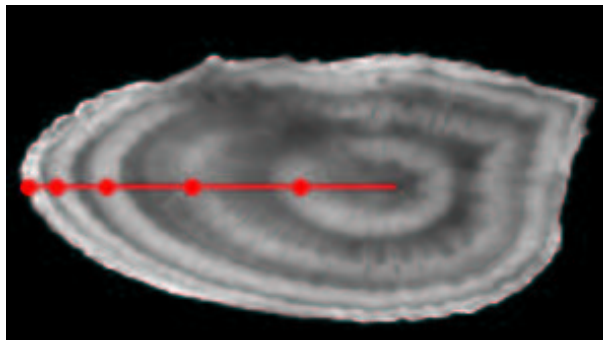


Figure 1. *Illustration of plaice otolith interpretation for a 4 year old individual. The otolith image has been acquired under a binocular with transmitted light. The interpretation of the translucent rings is displayed by the markers set on the radial drawn on the main reading axis from the center to the edge.*

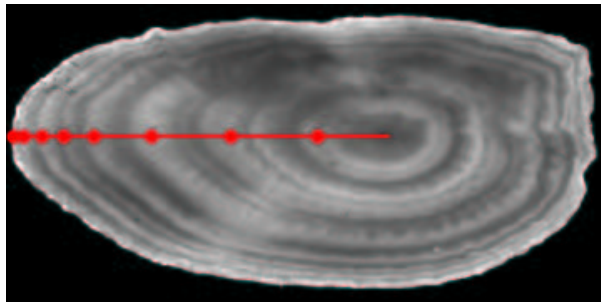


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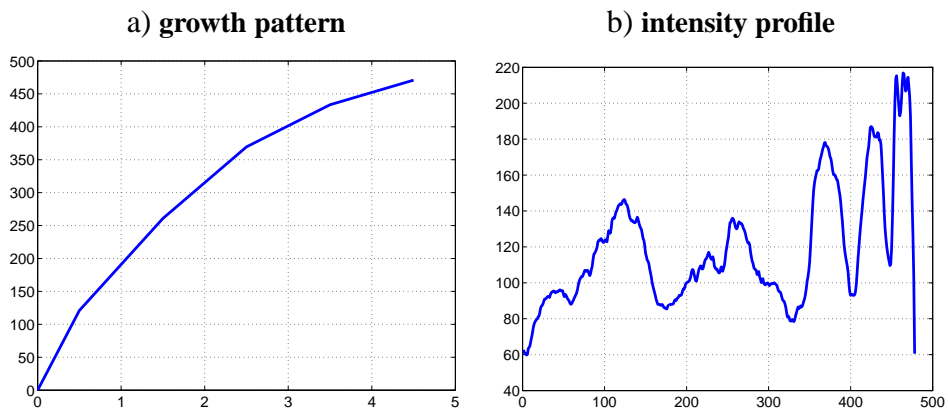


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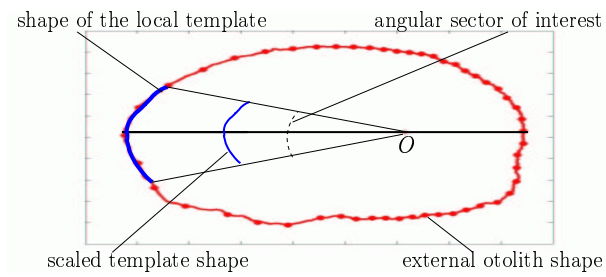


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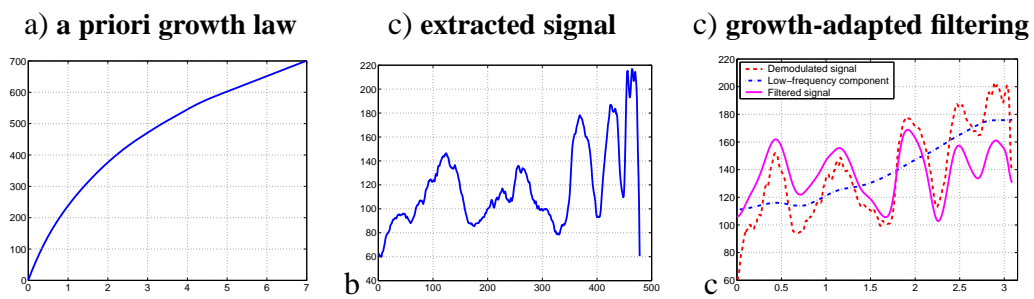


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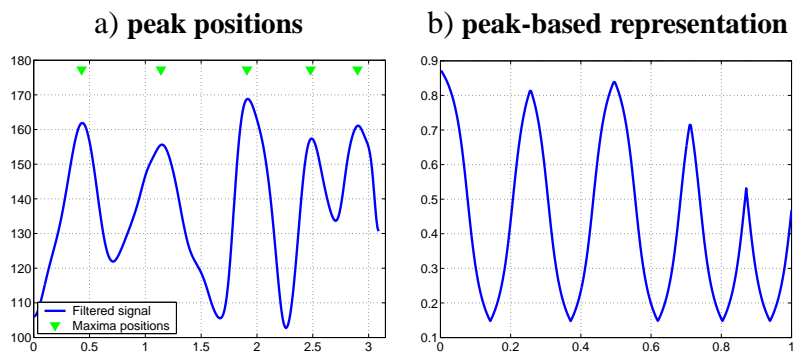
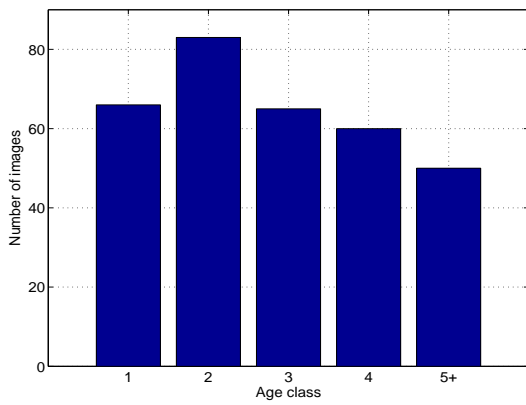


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a) age composition



b) growth variability

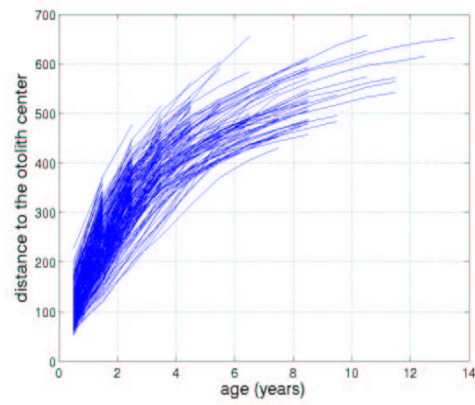


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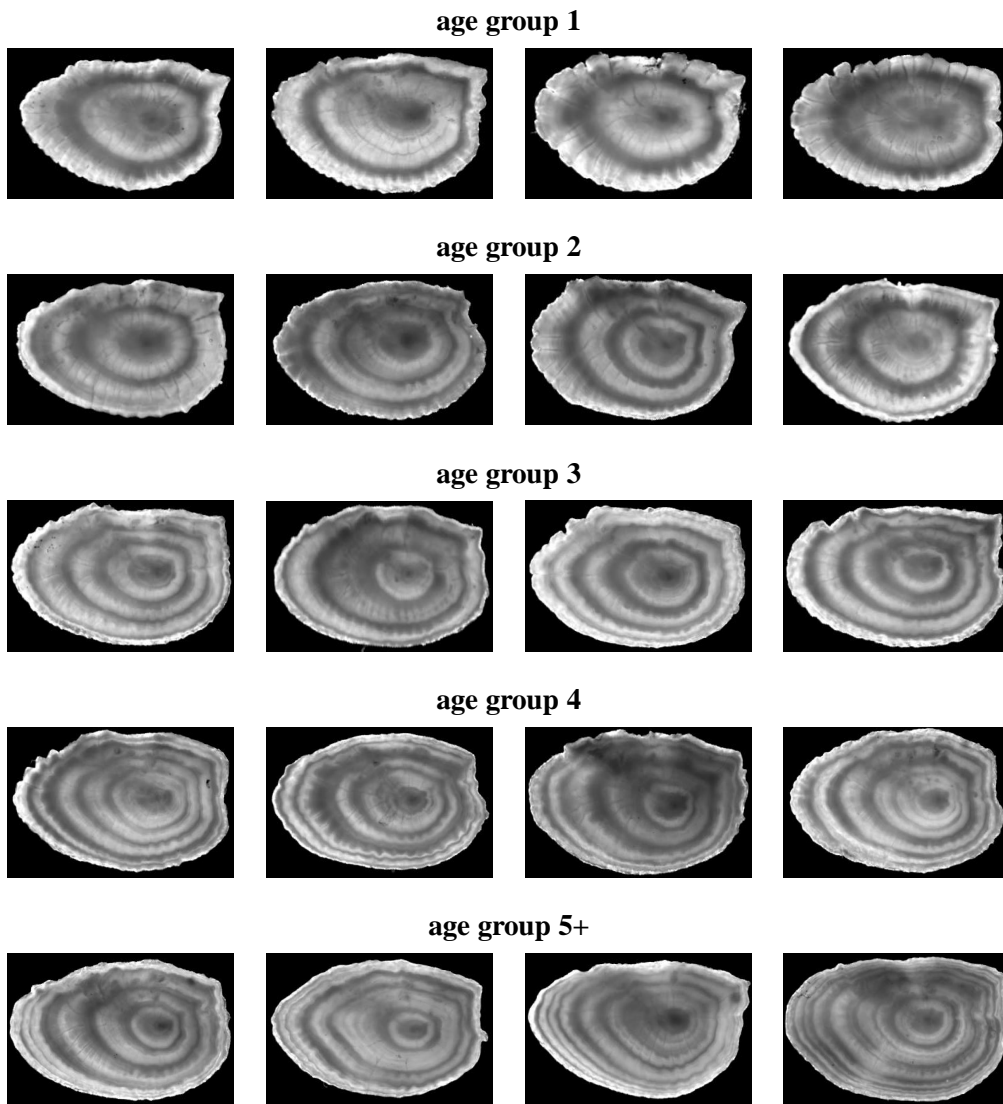


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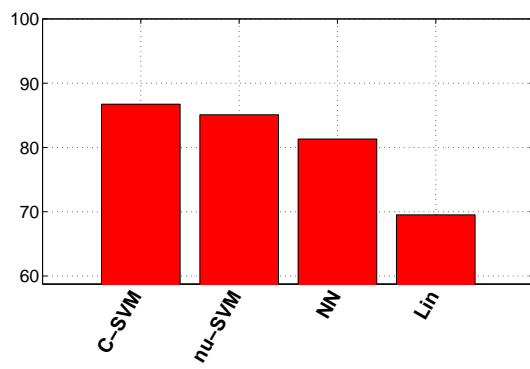


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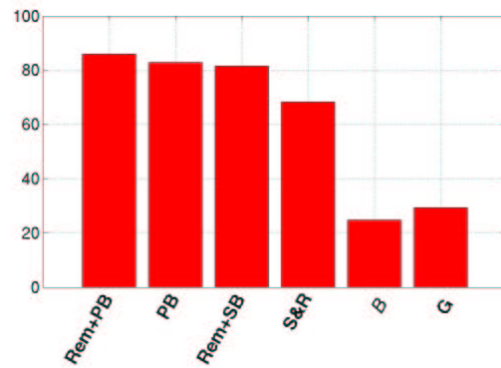


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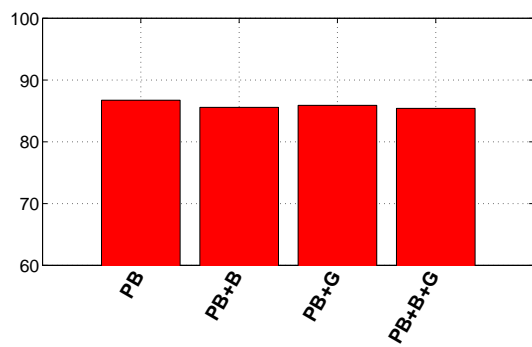


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516		non-overlapping angular sectors along the main reading axis. One	
517		should read the table as follows.) table	38

	1	2	3	4	5+	overall rate of errors in [-1,+1]
1	88.3 <i>88.3</i>	10 <i>10</i>	0.8 <i>0.8</i>		0.8 <i>0.8</i>	98.3 <i>98.3</i>
2		92.3 <i>90</i>	4.7 <i>7</i>	2.9 <i>2.9</i>		97 <i>97</i>
3		4.1 <i>4.1</i>	90 <i>92.5</i>	5.3 <i>3.3</i>		100 <i>96.6</i>
4		4.3 <i>5.2</i>	14.7 <i>14.7</i>	75.6 <i>73.9</i>	5.2 <i>6</i>	95.6 <i>94.7</i>
5+	1.1 <i>1.1</i>		7 <i>7</i>	8.2 <i>10.5</i>	83.5 <i>81.1</i>	91.7 <i>91.7</i>

Table 1

Confusion matrix of the results of fish aging over the test set using C-SVMs and the remodulation step for two feature types: peak-based features alone (bold) and the combination of peak-based and geometrical features (italic): for instance, 88.3% of the samples from class 1 are assigned to class 1, 10% to class 2, 0.8% to class 3 and 0.8% to class 5+.

	1	2	3	4	5+	overall rate of errors in [-1,+1]
1	91.6	8.3				100
2		91.1	5.8		2.9	97
3		4.1	91.6	4.1		100
4		4.3	13	78.2	4.3	95.5
5+			5.8	5.8	88.2	94.1

Table 2

Confusion matrix of the results of fish aging performed for each image of the test set by combining the classifications of five non-overlapping angular sectors along the main reading axis. One should read the table as follows.) table