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Pre-processing techniques applied to Automatic Taxon Identification on fish otoliths

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Abstract: This paper analyzes the characteristics of a rotation-invariant Feature space to be used in a classifier of fish otoliths, it is compared to two other Feature spaces, one with raw data and another with transformed data (using the Elliptic Fourier Descriptors EFD). Otoliths are found in the inner ear of fish. Their shape can be analyzed to determine sex, age, populations and species, and thus they can provide necessary and relevant information for ecological studies. The Automatic Taxon Identifier (ATI) is used to classify fish otoliths directly from a query image and is implemented on-line in a Public Database. This new Features space proposed in this study will allow the use of query images that are not normalized or are normalized in a different pose than the images in the Database. The rotation-invariant Feature space is the pre-processing part of a classifier based in kNearestNeighbours, and it is derived from the Elliptical Fourier Descriptors (EFD). The new Feature space compacts the information, and could be used when a feature reduction strategy is recommended. The authors analyze the classification results in a Test Database applying a controlled rotation to the Query images, and discuss their possible utility of the technique in the future ATI system.

Keywords: Otoliths, Feature space, Classifiers, Automatic Taxon Identification (ATI), Elliptic Fourier Descriptors (EFD), Pattern Matching, Pre-processing, Data mining

1 INTRODUCTION

Otoliths are calcareous structures found in the inner ear of Osteichthyan fishes. In ichthyology, the characteristics of otoliths (size, morphologic specificity, accessibility, chemical composition, microstructure and mode of growth) make them one of the most useful anatomic structures for various studies. Moreover, these otoliths properties depend on the variation in environmental and genetic factors (Castonguay et al. (1991)), which leads to a large number of practical applications like the ones that Campana et al (1993) or Lombarte et al. (1999). These applications are not limited to ichthyology, but are widely extended from the study of the feeding ecology of fish predators (the otoliths found in their stomach provide reliable information on their diet) to some aspects of palaeontology, stratigraphy, archaeology (as these structures can be fossilized) or even zoogeography.

In the last years the AFORO Project Team has developed an online otolith Database named AFORO (http://aforo.cmima.csic.es/) (Parisi-Baradad et al. (2005); Lombarte et al. (2006)) which is organized into high-resolution fish otolith images sets with complete morphometric information and includes a shape analysis module that provides mathematical descriptors of the otoliths like Fourier Transform (FT), Curvature Scale Space (CSS) and Wavelet Transform (WT). Parisi-Baradad et al. (2010) developed an Automated Taxon Identification (ATI) system that is able to classify external otolith images. There are several otoliths in the ear but the sagitta is the otolith with the largest morphologic variability, and therefore it is the most studied and the one selected for the AFORO Database. Throughout the text we will usually refer to any “sagitta otolith” as “otolith” for simplicity.
In this paper we focus on validating an improvement that could be added to the present ATI system. One of the main drawbacks of the system in its current form is its extreme sensitivity to the positioning of the otolith in the query image, especially when dealing with rotations and misalignments of the images. We will show that the system decreases drastically in performance when the images are not adjusted according to the protocol. To address this problem we propose the use of a new feature space that is a Transformed domain descriptor of the shape with built-in invariance to rotation. This approach would permit the use of the online system in different contexts, allowing a successful query to AFORO with images taken from a mobile device for example, with an arbitrary position of the otolith. The only requirement is that the image of the otolith is well contrasted with a black background. Our preliminary tests on 10 different species validate the suitability of the proposal.

2 MATERIALS AND METHODS

2.1 Test Dataset

The test material was taken from the AFORO Database. The Database is regularly updated and at present (03/22/2014) it contains a total of 4480 high resolution images corresponding to 1344 species and 216 families from the around the worlds’ Oceans. The specimens selected for the Database are focused on representing all the possible variability within each species, such as age, length, sex or stocks.

The approach presented in this paper has been tested with 117 otoliths from ten different species: Coris julius (COR), Engraulis encrasicolus (ENG), Pomadasys incisus (POM), two populations of the species Merluccius merluccius (from Catalonia and Galicia, CAT and GAL) from the family Merlucciidae, Scomber colias (SCC), Trachurus mediterraneus (TRM), Trisopterus minutus (TRI), Umbrina canariensis (UCA) and Umbrina cirrosa (UCI), represented in Figure 1, and summarized in Table 1. As it can be seen in Figure 1 the selection of the Test species was done including groups of species with similar shapes: for example COR, ENG, SCC and TRM; or the group of CAT, GAL, TRI; and the group POM, UCA and UCI; and thus making the problem more challenging and adjusted to real working conditions.

![Figure 1. (From left to right ) Left sagittal otoliths from COR, ENG, CAT (Catalonia), GAL (Galicia), POM, SCC, TRM, TRI, UCA and UCI.](image)

<table>
<thead>
<tr>
<th>Species</th>
<th>Shape</th>
<th>Range L</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coris julius</td>
<td>Cuneiform</td>
<td>85–255</td>
<td>11</td>
</tr>
<tr>
<td>Engraulis encrasicolus</td>
<td>Elliptic</td>
<td>110–155</td>
<td>10</td>
</tr>
<tr>
<td>Merluccius merluccius</td>
<td>Lanceolated to elliptic</td>
<td>80–730</td>
<td>14/14*</td>
</tr>
<tr>
<td>Pomadasys incisus</td>
<td>Oval to elliptic</td>
<td>150–350</td>
<td>14</td>
</tr>
<tr>
<td>Scomber colias</td>
<td>Kidney-shaped</td>
<td>172–405</td>
<td>11</td>
</tr>
<tr>
<td>Trachurus mediterraneus</td>
<td>Elliptic to fusiform</td>
<td>80–360</td>
<td>10</td>
</tr>
<tr>
<td>Trisopterus minutus</td>
<td>Spindle-shaped</td>
<td>100–240</td>
<td>14</td>
</tr>
<tr>
<td>Umbrina canariensis</td>
<td>Oval</td>
<td>140–530</td>
<td>10</td>
</tr>
<tr>
<td>Umbrina cirrosa</td>
<td>Oval</td>
<td>140–530</td>
<td>12</td>
</tr>
</tbody>
</table>

**Table 1.** Otoliths species in the Test Database with the corresponding characteristics: Shape, Size range of the fish in millimetres, number of elements in the Test Database. *(Two populations of Merluccius merluccius, one from Galicia and the other from Catalonia)*
2.2 Data collection, positioning protocol

*Image acquisition, positioning protocol*

The images are of the internal side (medial or proximal) of the entire otolith and the *sulcus acusticus* (a groove along the surface of the sagitta otolith) is always seen. Each otolith image is taken against a homogeneous black background to achieve good contrast, and therefore a good representation of the contour. The positioning protocol for the images is strict with the *Rostrum* on the right side and the main axis in horizontal position, as is explained in Lombarte (2006). The images are grayscale, 1 byte depth, and 640×480 pixels size. To characterize the otolith we extract the sequence of points of the outline. In the AFORO Database as all the images are highly contrasted any contour extractor works properly; in our case we have used a morphological contour extractor (Serra 1983); it is applied on the image after normalizing and binarizing it using an Otsu threshold detector (Otsu 1979), and the result are shown in Figure 3.

![Normalized otolith image (left side). Binarized otolith image with its contour (in red) inside an enclosing rectangular box (in green) (right side).](image)

**Figure 3.** Normalized otolith image (left side). Binarized otolith image with its contour (in red) inside an enclosing rectangular box (in green) (right side).

2.3 Scheme of the experimental ATI (Automated Taxon Identification)

The scheme to validate the approach is a simple ATI system, summarized in Figure 2. It consists of a k-Nearest Neighbour Classifier that compares the query Image to the whole Test Dataset and obtains the k closest images from there with a defined distance measure. In our experiments k is usually 3.

![Scheme of the ATI (Automatic Taxon Identification). The core consists in a k-Nearest Neighbor Classifier.](image)

**Figure 2.** Scheme of the ATI (Automatic Taxon Identification). The core consists in a k-Nearest Neighbor Classifier.

*k-Nearest Neighbour*

The k-Nearest Neighbours rule (kNN) defined by Cover et al. (1967) is one of the most well known and used nonparametric classifiers in Machine Learning and Data Mining tasks (Kononenko et al. (2007)). The simplest implementation involves finding the k closest neighbours of a query element inside the Database by comparing one by one in the feature space and with a distance metric defined in this space; once the k neighbours are selected the class of the query element is obtained for majority voting, in case of equality between classes the one with the minimum error is selected. In spite of its simplicity, it has demonstrated itself to be one of the most useful and effective algorithms in Data Mining (Papadopoulos et al.(2004)) and Pattern Recognition (Shakhnarovich et al.(2006); Wu et al.(2009)).

*Possible Feature space for the system; Pre-processing step.*

We use three different Feature spaces and all of them are calculated in the Pre-processing step:
The simplest one deals with the raw space of data, and uses the \( \{(x_n, y_n)\} \) sequences of the extracted contours to measure the distances between shapes. To simplify the comparison, all the contours are resampled to \( N=256 \) samples. The authors have fixed this value as it represents sufficient detail from the contours and it is a power of 2, adequate for an optimum Elliptic Fourier Descriptor (EFD) calculation.

Another Feature space explored is the transformed domain space, using the Elliptic Fourier Descriptor (EFD) of the contours. There is a wide consensus in Marine Biologist community to represent the otolith shape analysis with image contours and EFD, they used this approach from the first analysis in the field from Castonguay et al. (1991) and Campana et al. (1993). The details to compute the EFD coefficients can be found at Kuhl et al. (1982).

And finally, we implement an experiment with a Feature space that encompasses a built-in invariance to rotation that derives from the previous transformed Feature space. It will be introduced in the subsequent section.

### Distance measure in the Feature space

The metric distance from the query element to each one of the specimens in the Test Dataset is measured with the Euclidean distance in the Feature space. In the case of being in the raw coordinate space the distance between a query contour \( C^q \) and any other contour \( C^i \) could be expressed in equation (1):

\[
d(C^q, C^i) = \sqrt{\frac{1}{N} \sum_{n=0}^{N-1} (x^q_n - x^i_n)^2 + (y^q_n - y^i_n)^2}
\]

#### 2.5 Feature space Invariant to rotation.

Every sample of a two-dimensional one-pixel wide closed contour \( C^i \) \((x^i_n, y^i_n)\) can be written by its coordinates in the following matrix notation form of equation (2), \( \{a_k, b_k, c_k, d_k\} \) being the EFD coefficients.

\[
\begin{bmatrix}
x_n \\
y_n
\end{bmatrix} = \begin{bmatrix}
a_n \\
c_n
\end{bmatrix} + \sum_{k=1}^{N/2} \begin{bmatrix}
a_k & b_k \\
c_k & d_k
\end{bmatrix} \begin{bmatrix}
\cos\left(\frac{2\pi k}{N}\right) \\
\sin\left(\frac{2\pi k}{N}\right)
\end{bmatrix}
\]

(2)

The EFD Feature space compacts the information in the first coefficients. Each contour could be represented approximately with the first \( K \) coefficient (with \( K < N/2 \)), and the distance measure is expressed with equation (3):

\[
d(C^q, C^i) = \sqrt{\frac{1}{K} \sum_{n=1}^{K} (a^q_n - a^i_n)^2 + (b^q_n - b^i_n)^2 + (c^q_n - c^i_n)^2 + (d^q_n - d^i_n)^2}
\]

(3)

From (2) we can see that point \( (a_0, c_0) \) is the centre of masses of the contour. Changing the values of that point moves the contour to be centred at the new point and similarly, taking \( a_0=c_0=0 \) centres it at the origin of coordinates. If we rotate the contour by an arbitrary angle \( \theta \) and scale it by a factor \( A \) we have a new contour in terms of \( x_n \) and \( y_n \) expressed in equation (4):
\[
\begin{bmatrix}
  x_n \\
  y_n
\end{bmatrix} =
\begin{bmatrix}
  a_o \\
  c_o
\end{bmatrix} +
A \sum_{k=1}^{N/2}
\begin{bmatrix}
  \cos \theta & \sin \theta \\
  -\sin \theta & \cos \theta
\end{bmatrix}
\begin{bmatrix}
  a_k & b_k \\
  c_k & d_k
\end{bmatrix}
\begin{bmatrix}
  \cos \left(\frac{2\pi}{N}kn\right) \\
  \sin \left(\frac{2\pi}{N}kn\right)
\end{bmatrix}
\]  

(4)

So the new coefficients take the form of equation (5):

\[
\begin{bmatrix}
  a'_k & b'_k \\
  c'_k & d'_k
\end{bmatrix} =
A \begin{bmatrix}
  \cos \theta & \sin \theta \\
  -\sin \theta & \cos \theta
\end{bmatrix}
\begin{bmatrix}
  a_k & b_k \\
  c_k & d_k
\end{bmatrix}
= A
\begin{bmatrix}
  a_k \cos \theta + c_k \sin \theta & b_k \cos \theta + d_k \sin \theta \\
  -a_k \sin \theta + c_k \cos \theta & -b_k \sin \theta + d_k \cos \theta
\end{bmatrix}
\]  

(5)

Invariance to position could be achieved by considering a new set of coefficients with \( a_n = c_0 = 0 \). For example, \( e_k \) could be defined as is shown in equation (6):

\[
e_k = (a'_1)^2 + (c'_1)^2 + (b'_1)^2 + (d'_1)^2 \quad \text{for} \quad k = 1, \ldots, N/2 - 1
\]  

(6)

From the previous equations it is clear that the new coefficients are independent of angle \( \theta \), and therefore are the same as those obtained from equation (7):

\[
e_k = (a'_1)^2 + (c'_1)^2 + (b'_1)^2 + (d'_1)^2
\]  

(7)

To additionally obtain invariance to scale factor the new coefficients could be obtained following equation (8):

\[
f_k = \frac{(a'_1)^2 + (c'_1)^2 + (b'_1)^2 + (d'_1)^2}{(a'_1)^2 + (c'_1)^2 + (b'_1)^2 + (d'_1)^2} \quad \text{for} \quad k = 2, \ldots, N/2 - 1
\]  

(8)

In the new rotation-invariant Feature space, the information is more compacted than in the EFD space; the distance is defined with equation (9):

\[
C^i = \{f_2^i, \ldots, f_k^i\}
\]

\[
d(C^0, C^i) = \sqrt{\frac{1}{K-1} \sum_{n=2}^K (f_n^0 - f_n^i)^2}
\]  

(9)

### 2.6 Description of the experiments

To validate the new feature space we will compare the classification results inside the Test Database using the ATI scheme of figure 2 with the three different Feature spaces. The experiment involves using each one of the elements in the Test Database (1 to N-1) as a query image to the ATI and guessing its class (species). After that, we repeat the experiment with the query image rotated an angle value; we explore systematically the angle of rotation from 0º to 359º, and represent the mean classification success rate for each one of the angles for all the elements of the Test Database.
3 EXPERIMENTS AND RESULTS

Figure 4 shows the result of the experiment using the simplest Feature space, the raw contours coordinates, for an angle $\theta$ from 0º to 359º. The results are consistent with the general classification performance for the whole Database as can be seen in Parisi et al. (2010), and shows the extreme sensitivity with the rotation angle in the query images.

![Classification results for rotation angles from 0º to 359º, in a Feature space of raw coordinate data with 256 sample points.](image)

**Figure 4.** Classification results for rotation angles from 0º to 359º, in a Feature space of raw coordinate data with 256 sample points.

Figure 4 shows the effect of a rotation in the query image (from 0º to 359º) on the performance of the classifier; in this case the ATI uses the simplest feature space, the raw coordinates of each point of the contours, with 256 points, 512 features and, $x_n$ and $y_n$ values for each point. As seen in Figure 4 the performance of the classifier rapidly drops from 80% to less than 30% from rotation 25º to 27º.

A new experiment in the Figure 5 shows the result of the EFD Feature space, with 4, 8 and 32 coefficients, for rotation angle $\theta$ from 0º to 359º. The results show the compactness of EFD coefficients, with 32 values obtaining similar results to raw coordinates with 256 points.

![Classification performance using ELLIPTIC FOURIER DESCRIPTORS](image)

**Figure 5.** Classification performance using ELLIPTIC FOURIER DESCRIPTORS.
In Figure 5 the effect of rotation in the ATI is analyzed with the EFD Feature space, using 8, 16 and 32 coefficients. Better results seem to be achieved with more coefficients, but above 32 all the results are similar, this result curves have an even sharper fall from 75% to less than 30% from a rotation $9^\circ$ to $15^\circ$. The only advantage of the EFD space is its compactness respect with the raw coordinates, but it is even less robust to rotation angles in the query image.

Another experiment in the Figure 6 shows the result in the rotation invariant Feature space, for an angle $\theta$ from $0^\circ$ to $359^\circ$. We will analyze them in the next section. Figure 7 compares the best results in the same graph for each one of the Feature spaces.

![Figure 6](image)

**Figure 6.** Classification results for rotation angles from $0^\circ$ to $359^\circ$, in a rotation-invariant Feature space, using a simplified representation with 2, 3 and 5 coefficients.

Figure 6 shows effective invariance to rotation and the compactness of rotation-invariant Feature space, but with low performance of results compared to the other Feature spaces when there is no rotation.

![PARAMETERS COMPARISON ON CLASSIFICATION PERFORMANCE](image)

**Figure 7.** Classification results for the 3 Feature spaces, with rotation angles from $0^\circ$ to $359^\circ$.

One of the easily observed results from Figure 7 is that the rotation-invariant Feature space obtains its main characteristic, an effective invariance to rotation, but with a substantial prize: the classification results diminish to 50% in the best case (using 5 rotation-invariant coefficients), this value, according to the number of classes in the Test Dataset (11 classes) is quite a good result.
4 DISCUSSION

In this paper we present a pre-processing step that could be added to the current ATI system used to classify fish otoliths in order to eliminate its extreme sensitivity to the positioning of the otolith in a query image; especially when dealing with rotations and misalignments of the images. We have shown in Figures 4 and 5 how the system based on classical Feature spaces (raw and EDF) decreases drastically in performance when the images are not adjusted according to the protocol. To address this problem we propose the use of a new feature space that is a Transformed domain descriptor of the shape with built-in invariance to rotation.

When comparing the three Feature spaces (Figure 7) we see that with rotation angles from 0 to 20° the raw coordinates Feature space outperforms the others, however for higher rotation angles the rotation-invariant coefficients are by far the best option. Another aspect that must be taken into account is the number of coefficients needed in the Feature space to represent a contour. As can be seen in Figure 5, 6 and 7, the transformed Feature spaces represent almost the same information as the raw coordinates with fewer elements. Moreover the rotation-invariant coefficients compact more the information than the EFD coefficients.

This approach would permit the use of the online ATI system in different contexts; the only requirement is that the image of the otolith is well contrasted with a black background. The misalignment and rotation of images is a very common problem in real world situations when using an ATI system: i.e. the positioning could be operator dependent in some species of otoliths, because many of them are very similar, and the singular points could be easily interpreted differently by different operators. Another advantage could be that collections obtained with different positioning could be mixed up. Other possibilities include the use of the system by non-expert users, they can query an otolith in any position, even with the surcus in a wrong position, allowing a successful query to AFORO with images taken from a mobile device for example, with an arbitrary position of the otolith. Our preliminary test on 10 different species validates the suitability of the proposal.

The future work regarding this experiment will be to extend it to a bigger Dataset, but there will be a deeper analysis in order to develop new strategies to extend the obtained results with higher classification results, similar to the ones with the normalized images.

REFERENCES


