Clupea Harengus: Intraspecies Distinction using Curvature Scale Space and Shapelets

Classification of North-sea and Thames Herring using Boundary Contour of Sagittal Otoliths

James Mapp[1], Mark Fisher[1], Anthony Bagnall[1] Jason Lines[1], Sally Songer[2] and Joe Scutt Phillips[2]
[1]*School of Computing Sciences, University of East Anglia, Norwich Research Park, Norwich, England, U.K.*
[2]*CEFAS Laboratory, Pakefield Road Lowestoft, Suffolk NR33 0HT, U.K.*

Keywords: CSS, Curvature, Scale-space, Shapelets, Otolith, Intraspecies, Classification, Random-forrest, Image-processing, LOOCV, Cross-validation.

Abstract: We present a study comparing Curvature Scale Space (CSS) representation with Shapelet transformed data with a view to discriminating between sagittal otoliths of North-Sea and Thames Herring using otolith boundary and boundary metrics. CSS transformed boundaries combined with measures of their circularity, eccentricity and aspect-ratio are used to classify using nearest-neighbour selections with distance being computed using CSS matching methods. Shapelet transformed data are classified using a number of techniques (Nearest-Neighbour, Naive-Bayes, C4.5, Support Vector Machines, Random and Rotation Forest) and compared to CSS classification results. Both methods use Leave One Out Cross Validation (LOOCV). We describe the method of encoding and the matching algorithm used during CSS classification and give an overview of Shapelet transforms and the classifiers that are used on the data. It is shown that whilst CSS forms part of the MPEG-7 standard and performs better than random selection, it can be significantly out-performed by recent additions to machine-learning methods in this application. Shapelets also show that with regard to intra-species distinction, the discriminatory features of otolith boundaries may lie not in the major inflection points, but the boundary points between them.

1 INTRODUCTION

Otoliths are calcium carbonate structures present in many vertebrates and found within the sacculus of the pars inferior. Whilst there are three types of otoliths; sagittae, lapilli and asterisci, found in each chamber of fishes, it is primarily the sagittal otoliths that are used in studies as they are larger and thus easier to prepare and observe. They vary markedly in shape and size between species, but are of similar shape compared to other stocks of the same species (Figure 1). Otoliths hold information that can be used by 'expert readers' to determine several key factors.

Some of these determinations however are harder to distinguish and (arguably) more critical to fisheries scientists or fisheries authorities (Begg et al., 2005). Such management requires that stocks be accurately determined (Stransky, 2005) so that decisions on their management can be made. Analysis of otolith boundaries may allow estimation of stock composition, determining whether the samples obtained from an area or areas are all in fact from one stock, or from multiple stocks mixed together (Duarte-Neto et al., 2008; Campana and Casselman, 1993; DeVries et al., 2002).

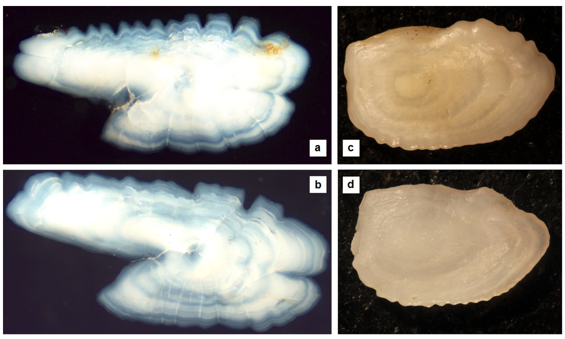

Figure 1: Otoliths from North-Sea Herring (a), Thames Herring (b) and two distinct populations of Plaice (c and d).

Mapp J., Fisher M., Bagnall A., Lines J., Warne S. and Scutt Phillips J. (2013).
Clupea Harengus: Intraspecies Distinction using Curvature Scale Space and Shapelets - Classification of North-sea and Thames Herring using Boundary Contour of Sagittal Otoliths.
In *Proceedings of the 2nd International Conference on Pattern Recognition Applications and Methods*, pages 138-143
DOI: 10.5220/0004226101380143

Currently for more advanced classification tasks such as age determination or stock identification, otoliths samples are often prepared by segmenting and polishing (Begg et al., 2001; Bolle et al., 2004). Our study focuses on whether fish from two stocks (North-Sea and Thames) of the same species (Herring) can be classified using otolith boundaries alone.

Collections of otolith specimens were prepared by the Centre for Environment, Fisheries and Aquaculture Science (CEFAS). The set of images includes populations of Herring from two distinct stocks, North-Sea and Thames Herring and have been labelled by CEFAS. The set also includes a number of images of Plaice otoliths which we use when testing the system. The captured images were received with no information other than the population to which they belong.

This paper compares two methods of image boundary representation: Curvature scale space, part of the MPEG-7 standard (MPEG-7, 2003); and Shapelets, a new method first proposed by Eamonn Keogh's research group (Ye and Keogh, 2009) and recently extended by UEA's machine learning group (Lines et al., 2012). The CSS-transformed data are classified using the standard CSS matching algorithm, whereas the Shapelet data are classified using a number of methods; Nearest-Neighbour, Naive-Bayes, C4.5, Support Vector Machines (linear and Quadratic), Random Forest and Rotation Forest.

2 SHAPE REPRESENTATION

2.1 Image Segmentation and Boundary Extraction

Before encoding can be implemented the boundary of each otolith must be identified. Images are segmented using simple supervised thresholding scripted in MATLAB R2010b (MATLAB, 2010). The boundary is then determined by performing a logical 'OR' function between the denoised mask and a morphological dilation of the mask using a square 3x3 structuring element. Each boundary is encoded as a set of boundary pixel coordinate pairs and stored in a data structure, with elements representing the coordinate arrays, image path, and the class. The upper-leftmost point/pixel on the boundary is used as the start point and coordinates are extracted in a counter-clockwise direction in all cases. Boundaries are normalised so that the origin is located at the boundary centroid, and subsampled to five-hundred equally spaced boundary points.

2.2 CSS Image Construction

Curvature Scale-Space (CSS) (Mokhtarian and Mackworth, 1992) forms the basis for contour-based shape descriptors within MPEG-7 (Bober, 2001; Zhang and Lu, 2003b; Zhang and Lu, 2003a). As such it forms an ideal starting point for boundary based shape classification of otoliths and has been used for several other studies in this field (Parisi-Baradad et al., 2005; Abbasi et al., 1999; Jalba et al., 2006). Research has shown that CSS encoding and its attributed matching algorithm can be an effective and robust (to noise, scale, rotation) method of matching query images to database models when combined with global parameters such as Circularity and Eccentricity (Abbasi et al., 1999; Amanatiadis et al., 2011).

In addition to intraspecies distinction, we also discriminate between two species of fish (Herring and Plaice) and on classes from the MPEG-7 SHAPE database (MPEG7, 1999) with a view to benchmarking our CSS implementation. The SHAPE database contains 20 images per class for 70 classes, and was developed for testing MPEG-7 shape descriptors. For use in our study we remove the 'device' classes as they hold deliberate within class variance. We also exclude the 'spring' class as the shape itself causes problems when creating CSS data.

The CSS images are constructed using the procedure laid out in previous work (Abbasi et al., 1999). The process involves iteratively smoothing the original boundary curve of the image using a 1-D Gaussian function of increasing kernel width and, after each iteration, computing the curvature of the boundary and where the curvature 'crosses' zero. This process continues until there are no remaining zero-crossings on the boundary, and stored as coordinate pairs (maxima) representing the points along the boundary and the iteration or "evolution" at which zero-crossings converge.

As in previous work we initiated the process using a kernel width (σ) of 1, increasing by 0.1 after each evolution, and compute a small number of global metrics to assist in the matching process (Mokhtarian et al., 1996; Abbasi et al., 1999): Circularity and Eccentricity (of the boundary); and Aspect-Ratio (of the CSS image created during the process).

2.3 Time Series Shapelets

A Shapelet is a time series data mining primitive that can be used to measure similarity between series based on small common shapes that occur at any point in the series. The original work on Shapelets was presented in (Ye and Keogh, 2009), where a recursive decision tree algorithm is presented using Shapelets as the branching criteria. Of particular interest is the work in (Lines et al., 2012), where it is proposed that Shapelets can be used to construct a filter for transforming time series data. Transforming data in this manner moves away from the previous emphasis of tree-based classification, allowing any traditional classification algorithm to be used with Shapelets.

We use the Java implementation of (Lines et al., 2012) to build a filter for transforming the Herring boundary data. The implementation utilises information gain to test the discriminatory power of a Shapelet. To initialise the filter, three parameters are required: minimum/maximum Shapelet lengths, and the number of Shapelets to be extracted. We extracted the best 100 Shapelets between the lengths of 40 and 120 from the dataset for the transformation process. This transformation is then carried out for each boundary by calculating the distance from the series to each of the extracted Shapelets, and each distance is used as an attribute in the transformed data.

3 CLASSIFICATION

3.1 CSS Classification

With each boundary stored as the locations of its curvature-crossing maxima, images can be compared to one another using previously defined methods (Abbasi et al., 1999; Mokhtarian et al., 1996). This results in a measure of similarity between the two sets of maxima and can be used to compare one *image* to a number of *model*s in a database and find the *model* with the greatest similarity. We are able to dismiss a number of models by comparing the CSS image/model aspect-ratios as well as the circularity and eccentricity metrics, dismissing as dissimilar any pairs with metric ratios greater than a given threshold (T).

Tests are performed using multiple values for T on both the Herring and SHAPE datasets. Initially it was thought that T may be pattern independent. The results show that optimum T values are significantly different between the two data sets, and use of one on the other set would result in significant underperformance. As in (Abbasi et al., 1999) we set allignments for all maxima $\geq 80\%$ of the largest evolution level, however we use a more generous matching distance at 40% of maximum distance.

CSS classification is performed using Nearest-Neighbour (NN) selection, with model distances equal to their dissimilarity. The set of images is tested using LOOCV and results returned as a percentage of selections that resulted in the correct class. Classification using the same methods are carried out on images from the MPEG-7 SHAPE database to benchmark our CSS implementation. For comparison we also process otoliths of Plaice (*Pleuronectes platessa*) alongside Herring otoliths (HvP) to determine whether inter-species distinction is possible using the same method.

3.2 Boundary and Shapelet Classification

We use LOOCV when classifying both the Univariate Boundaries (UV-Bs) and Shapelet transform thereof, using a variety of available classifiers so that results of transformed and non-transformed boundaries can be compared. CSS maxima (as Boundary-Point/Evolution pairs) are tested using the same classifiers in addition to using the standard CSS matching procedure in order to evaluate the matching method itself. Two datasets are created for this testing; CSSa (maxima sorted by distance along the boundary) and CSSb (by evolution magnitude). The classifiers used on these sets are implemented in the Java Machine Learning toolkit WEKA (Hall et al., 2009) and are; 1-Nearest Neighbour with Euclidean distance (NN), Naive Bayes (NB), C4.5 Decision Tree (C4.5), Support Vector Machines with a linear/quadratic kernels (SVML/SVMQ), Random Forest ensemble with 100 base classifiers (RaF), Rotation Forest ensemble with 30 base classifiers (RoF), 1-Nearest Neighbour with dynamic time warping distance, performed on UV-OL data only (NNDTW).

4 RESULTS

4.1 CSS Classification

Results from classification using the CSS matching implementation can be seen in Figures 2 and 3. The figures show results given eccentricity, circularity and aspect-ratio thresholds in the range 0 to 0.40. It can be seen that the thresholds returning peak performance in these cases are significantly different to one another, and use of one problem's optimised threshold value for the other would result in under-performance.

In all cases the inclusion of a threshold for the global parameters improve, or at least do not hinder, accuracy. Table 1 shows results of the two classifications using no threshold (where $T=1$), and when using the peak performance global threshold (value for

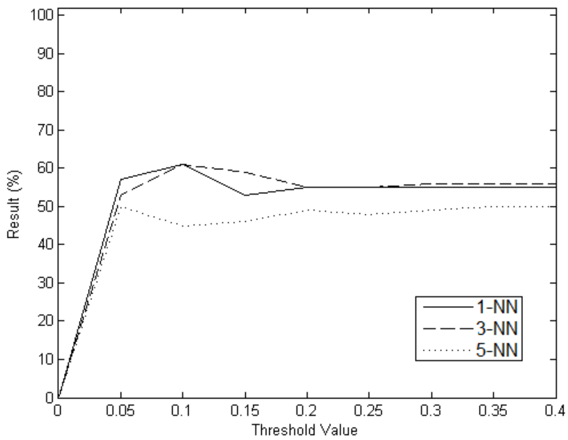

Figure 2: Graph showing results of NorthSea/Thames Herring classification using 1, 3 and 5-NN over multiple threshold values.

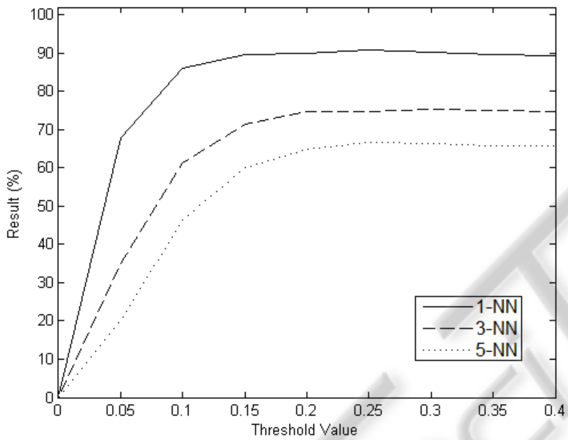

Figure 3: Graph showing results of SHAPE database image classification using 1, 3 and 5-NN over multiple threshold values.

each case given in table). Alongside are shown results when classifying Herring/Plaice otoliths (interspecies distinction) both with and without peak values for *T*.

Table 2 shows sensitivity and specificity (or Sensitivity NS and Sensitivity Th) of the CSS matching algorithm. The figures show that the CSS matching technique is generally more sensitive to Thames Herring otoliths than to North Sea otoliths. The table shows results for using both peak performance threshold, and no threshold (divided by the double vertical lines).

The increase in accuracy, sensitivity and specificity when global thresholds are implemented supports the idea that the two classes of boundary have significant overlap in scale space, where boundaries that show differences while unprocessed may have much the same representation.

Table 1: The LOOCV classification accuracies using our CSS matching implementation on all three tests, North-Sea Vs Thames (NSvTh), Classes from the SHAPE database (SHAPE) and Herring Vs Plaice (HvP).

		1-NN	3-NN	5-NN
NSvTh	T = 1	55%	56%	50%
	peak T = 0.01	61%	61%	45%
SHAPE	T = 1	87%	69%	59%
	peak T = 0.25	91%	74%	67%
HvP	T = 1	100%	99%	100%
	peak T = 0.20	100%	100%	100%

Table 2: Confusion matrices including sensitivity (Se) and Specificity (Sp) for NSvTh classification using 1,3 and 5-NN selection (Rows - Query, Columns - Result). Table to the Left using peak T value, to the right using no threshold (T=1).

		NS	Th	Se/Sp	NS	Th	Se/Sp
1-NN	NS	26	24	0.52	21	29	0.42
	Th	15	35	0.70	16	34	0.68
3-NN	NS	29	21	0.58	25	25	0.50
	Th	18	32	0.64	19	31	0.62
5-NN	NS	24	26	0.48	25	25	0.50
	Th	29	21	0.42	25	25	0.50

4.2 Shapelet Classification

The results in Table 3 demonstrate promising classification results using the Shapelet-transformed data. The best performing classifier on this data is the Random Forest algorithm, which was over 20% more accurate than using a simple one-nearest neighbour approach. It is also interesting to note that the standard decision tree implementation using C4.5 is outperformed by the simple Naive Bayes classifier. The Table also shows results of the same classification algorithms using Univariate Boundary-data (UV-B) and CSS maxima ‘coordinate’ pairs (CSSa and CSSb).

Table 3: The LOOCV classification accuracies of a range of algorithms using Univariate Boundary data (UV-B), Shapelet transformed data (Shapelet) and CSS maxima (CSSa/CSSb).

Classifier	UV-B	Shapelet	CSSa	CSSb
NN	58%	64%	55%	49%
NB	63%	77%	55%	50%
C4.5	56%	74%	46%	56%
SVML	59%	75%	65%	70%
SVMQ	58%	71%	59%	67%
RaF	68%	87%	54%	54%
RoF	61%	78%	52%	52%
NN - DTW	65%	N/A	N/A	N/A

From the top five Shapelets it was seen that the discriminating features determined by Shapelet encoding fall in areas of very low curvature. This may explain the comparatively poor results produced by the CSS method on HvH tests, where the same system performs well on other datasets. If discriminatory portions of the boundary mainly fall in areas of low curvature, then curvature modelling techniques will have difficulty distinguishing between the two classes. Also where discriminatory features depend on angle of section with respect to the boundary centroid or other sections of the curve, CSS methods will be unable to distinguish between them as curvature maxima give no indication of angle with respect to non-regional areas. It is noted however that using curvature maxima did offer some improvement on random selection, therefore maxima must offer some level of discriminatory power.

5 CONCLUSIONS

Our study has shown that curvature scale space works well for classification where class boundaries are significantly different (between species or between classes of the SHAPE database). Nearest-Neighbour classification of Herring performed better using UV-Bs than the CSS transformed data alone (CSSa, CSSb in Table 3), the use of CSS's own matching algorithm and global thresholds increase accuracy further, to around the same accuracy as other classification methods (of UV-Bs). Even the best CSS encoding/classifying method is significantly outperformed by Shapelet method of encoding regardless of which classifier is used to process data. The method offers accuracy (3-26% better), sensitivity and specificity far above the CSS matching methods used.

Our results compare well with previous studies of stock discrimination using otoliths. Studies of dolphinfish otoliths (Duarte-Neto et al., 2008) using fourier desciptors of the boundary show results in the region 57-70% which is comparable to our CSS matching implementation. Campana and Casselman (Campana and Casselman, 1993) produce results of 67% using otolith boundary alone, however other results in the same study fall far below those discussed in this work. Results from mackerel classification (DeVries et al., 2002) show 80-86% accuracy which while significantly above our CSS implementation, compares well with our shapelet classification results. Our shapelet approach also matches the accuracies of studies which use microstructure analysis (Petursdottir et al., 2006), and where shape alone returned results equal to or lower than our CSS methods.

Results from tests on the SHAPE database compare well with previous work (Abbasi et al., 1999; Latecki et al., 2000). Whilst our results have shown a moderate (15%) improvement on those results it should be noted that we have excluded several classes from our SHAPE set, and some previous results are given with restricted sets themselves.

6 FURTHER WORK

For the purpose of this study we have returned results using multiple values for the global threshold. However this threshold itself is used for three different global measures; circularity, eccentricity and maxima aspect-ratio, rather than each having their own limit. Further work should attempt to better utilise the three metrics. Existing and subsequent metrics should be assessed individually for effectiveness rather than using a single threshold. Whilst we have determined that the threshold cannot be set using separate (SHAPE) datasets, the threshold itself should be set using some form of double-cross validation if possible (Stone, 1974) to avoid overfitting the threshold or thresholds to the specific classification problem.

As Shapelets appear to show that important information is available in areas of low curvature, it is possible that methods to enhance CSS for shapes with shallow concavities (Abbasi et al., 2000) may increase classification accuracy. We plan to compliment the method used with these enhancements to determine whether they are suitable for our problem. It may be further possible that other enhancement methods such as those that encode convex shapes (Kopf et al., 2005) improve results using the CSS matching technique.

REFERENCES

Abbasi, S., Mokhtarian, F., and Kittler, J. (1999). Curvature scale space image in shape similarity retrieval. *Multimedia systems*, 7(6):467–476.

Abbasi, S., Mokhtarian, F., and Kittler, J. (2000). Enhancing css-based shape retrieval for objects with shallow concavities. *Image and Vision Computing*, 18(3):199–211.

Amanatiadis, A., Kaburlasos, V., Gasteratos, A., and Papadakis, S. (2011). Evaluation of shape descriptors for shape-based image retrieval. *Image Processing, IET*, 5(5):493–499.

Begg, G., Campana, S., Fowler, A., and Suthers, I. (2005). Otolith research and application: current directions in innovation and implementation. *Marine and Freshwater Research*, 56(5):477–483.

Begg, G., Overholtz, W., Munroe, N., et al. (2001). The use of internal otolith morphometrics for identification of haddock (melanogrammus aeglefinus) stocks on georges bank. *Fishery Bulletin*, 99(1).

Bober, M. (2001). Mpeg-7 visual shape descriptors. *Circuits and Systems for Video Technology, IEEE Transactions on*, 11(6):716–719.

Bolle, L., Rijnsdorp, A., van Neer, W., Millner, R., van Leeuwen, P., Ervynck, A., Ayers, R., and Ongenae, E. (2004). Growth changes in plaice, cod, haddock and saithe in the north sea: a comparison of (post-) medieval and present-day growth rates based on otolith measurements. *Journal of sea research*, 51(3):313–328.

Campana, S. and Casselman, J. (1993). Stock discrimination using otolith shape analysis. *Canadian Journal of Fisheries and Aquatic Sciences*, 50(5):1062–1083.

DeVries, D., Grimes, C., and Prager, M. (2002). Using otolith shape analysis to distinguish eastern gulf of mexico and atlantic ocean stocks of king mackerel. *Fisheries Research*, 57(1):51–62.

Duarte-Neto, P., Lessa, R., Stosic, B., and Morize, E. (2008). The use of sagittal otoliths in discriminating stocks of common dolphinfish (coryphaena hippurus) off northeastern brazil using multishape descriptors. *ICES Journal of Marine Science: Journal du Conseil*, 65(7):1144–1152.

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., and Witten, I. (2009). The weka data mining software: an update. *ACM SIGKDD Explorations Newsletter*, 11(1):10–18.

Jalba, A., Wilkinson, M., and Roerdink, J. (2006). Shape representation and recognition through morphological curvature scale spaces. *Image Processing, IEEE Transactions on*, 15(2):331–341.

Kopf, S., Haenselmann, T., and Effelsberg, W. (2005). Enhancing curvature scale space features for robust shape classification. In *Multimedia and Expo, 2005. ICME 2005. IEEE International Conference on*, pages 4–pp. IEEE.

Latecki, L., Lakamper, R., and Eckhardt, T. (2000). Shape descriptors for non-rigid shapes with a single closed contour. In *Computer Vision and Pattern Recognition, 2000. Proceedings. IEEE Conference on*, volume 1, pages 424–429. IEEE.

Lines, J., Davis, L., Hills, J., and Bagnall, A. (2012). A shapelet transform for time series classification. In *Proc. 18th ACM SIGKDD*.

MATLAB (2010). *version 7.11.0 (R2010b)*. The MathWorks Inc., Natick, Massachusetts.

Mokhtarian, F., Abbasi, S., and Kittler, J. (1996). Robust and e cient shape indexing through curvature scale space. In *Proceedings of the 1996 British Machine and Vision Conference BMVC*, volume 96.

Mokhtarian, F. and Mackworth, A. (1992). A theory of multiscale, curvature-based shape representation for planar curves. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 14(8):789–805.

MPEG-7 (2003). Multimedia content description interfaces. part 6: Reference software. ISO/IEC 15938-6.

MPEG7 (1999). Ce shape-1 part b, 1400 binary shape images.

Parisi-Baradad, V., Lombarte, A., García-Ladona, E., Cabestany, J., Piera, J., and Chic, O. (2005). Otolith shape contour analysis using affine transformation invariant wavelet transforms and curvature scale space representation. *Marine and freshwater research*, 56(5):795–804.

Petursdottir, G., Begg, G., and Marteinsdottir, G. (2006). Discrimination between icelandic cod (gadus morhua l.) populations from adjacent spawning areas based on otolith growth and shape. *Fisheries research*, 80(2):182–189.

Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 111–147.

Stransky, C. (2005). Geographic variation of golden redfish (sebastes marinus) and deep-sea redfish (s. mentella) in the north atlantic based on otolith shape analysis. *ICES Journal of Marine Science: Journal du Conseil*, 62(8):1691–1698.

Ye, L. and Keogh, E. (2009). Time series shapelets: A new primitive for data mining. In *Proc. 15th (ACM SIGKDD)*.

Zhang, D. and Lu, G. (2003a). A comparative study of curvature scale space and fourier descriptors for shape-based image retrieval. *Journal of Visual Communication and Image Representation*, 14(1):39–57.

Zhang, D. and Lu, G. (2003b). Evaluation of mpeg-7 shape descriptors against other shape descriptors. *Multimedia Systems*, 9(1):15–30.