Evaluating the Efficacy of Probabilistic Neural Networks to Determine Stock Structure in Sockeye Salmon Using Fourier Transformed Luminance Profiles of Scale Circuli

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Patterns of circuli groupings within scales are used to determine the stock structure of sockeye salmon (*Oncorhynchus nerka).* The methodology typically employed involves using trained scale readers to interpret and manually measure circuli spacing patterns. These measurements are used as input into Linear Discriminant function Analysis (LDA) to determine stock structure. This pilot study introduces a new technique, probabilistic neural networks, to evaluate scale patterns for stock composition. We compare the method directly to LDA by using the same measurement data as input. We then explore Fourier analysis of luminance profiles of the scale images as an objective means to classify scale patterns. The samples used in the pilot study are from two Canadian stocks and one Alaskan stock encountered in South-east Alaskan fisheries. Correctly identifying these stocks has been a challenging problem for fisheries management.

The probabilistic neural networks (PNNs) used for this study were implemented using proprietary software (Ward Systems Neuroshell®). PNNs are intrinsic classification models and are known for their ability to quickly train (Masters 1993). The PNN categorised the frequency transformed luminescence profiles from scales into one of three output categories, each representing a discrete stock. The PNN provides a probability density function of stock-membership as an output where the most probable stock identification is classified in the output vector as the element with the highest value. A 'sphere of influence' weighting function, a multi-variate extension of Parzen's method (Masters 1995), is used to map the inputs to their respective output. The width of the 'sphere of influence' is determined by a scaling parameter that varies between input variables. As there is no objective method for determining the size of this scaling parameter (Masters 1994), Neuroshell® software uses a 'genetic' algorithm for determining the optimum size of the scaling parameter for each input element.

A total of 599 scale samples were obtained as acetate impressions from US and Canada sampling projects by ADFG in 2002. These include 200 samples from nine areas within Alaska, 199 samples from the Nass River system and 200 from the Skeena River system in Canada. They were analysed as mixed stock samples with LDA following established procedures that use scale measurement data to estimate stock composition of commercial catches (Bloomquist et al. 2002). Digital images of the scales (8 bit, 14.8 M pixels) were obtained with a digital microfiche system designed for scale analysis (Hagen et al. 2001) and transmitted electronically in JPEG 2000 format along with the scale measurement data and the associated sampling data (area of capture, length, age and sex) to CAF laboratory in Australia. No information was available on the sex of the Skeena River samples.

To create datasets for PNN analysis in this study, the images were reduced to 1.1M pixels using Leadtools File Converter™ and selected for further analysis where the impression was suitable for extraction of pixel data. Subsequently, the number of samples used for analysis was 199, 199 and 191 (n = 589) for the Alaskan, Nass River and Skeena River area of capture respectively. Optimas™ image analysis software was to draw six transects from the focus of each scale, radiating in approximate equal steps around the posterior region of the scale (Fig. 1). From each transect, luminance profiles were extracted from the first 128 pixels or sampling points (Fig. 2). This distance covered the period of freshwater growth, but did not cover the first marine annulus as did the measurement data.

The grey scale values in the profiles were collected as complex numbers using the Discrete Fast Fourier Transformation, (FFT, Equation 1). To minimise spectral leakage from the FFT, it was necessary to window the data. This was accomplished using the Welch window (Equation 2, Fig. 3). This is needed as the FFT assumes the time domain sample is periodic, and is captured over an integral number of periods (the end of the series implicitly wraps to the beginning). This is not the case with transect data.

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Fig. 1. Acetate scale impression from an Alaskan sockeye salmon (AK0212U0001) sampled from Hugh Smith Lake (490 mm mid-eye to fork length, ♂). Ideal location of transects shown (T1-T6). The number postscripts represent the marking sequence. Transect location varied by up to approximately 10 degrees from the ideal transect locations. Mark {A} represents the approximate length of 128 pixels from the biological center of the scale.

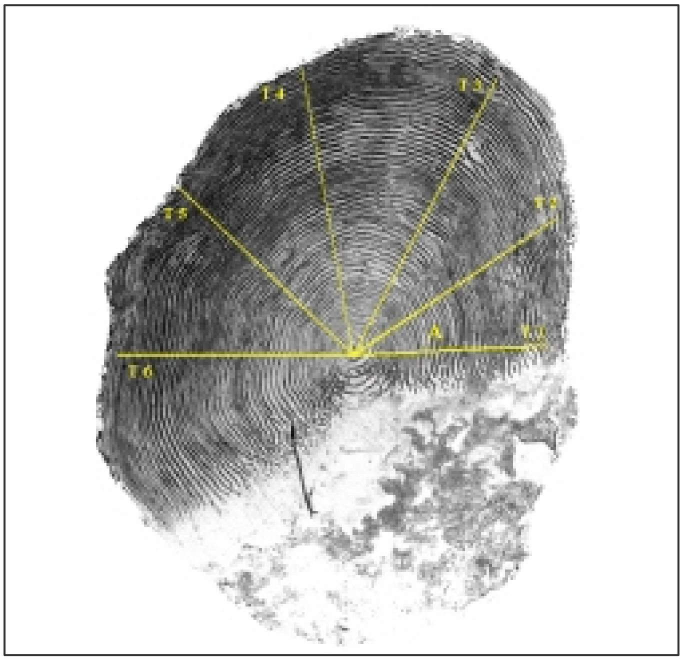
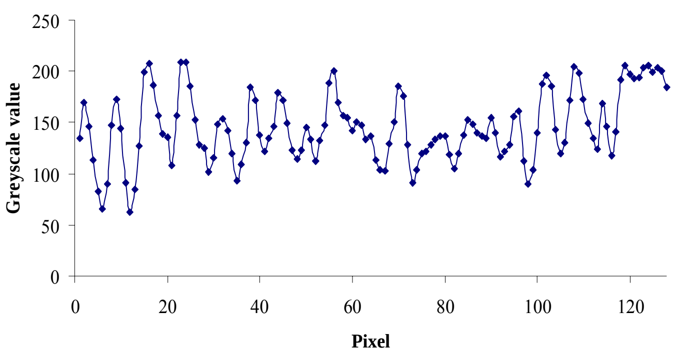


Fig. 2. Extracted Luminance profile (T1) from a sockeye salmon (AK0212U0001) scale acetate press sampled from Hugh Smith Lake (490 mm mid-eye to fork length, ♂).



The data was transformed into the time domain using the inverse FFT (Equation 3). The pixel values were multiplied by the Welch window and transformed back to the frequency domain. The power (harmonics) of the Fourier series was calculated as the absolute value of the complex number (Equation 4). Since reconstruction of the original luminance profile from the transect which was adequately described using 21 complex numbers (Fig. 4), the power from the first 21 complex numbers was used as inputs to the network (Fig. 5). Network models were tested using harmonics from single transects and combinations of transects; both with and without length and sex data (Table 1). Sex data was treated as categorical inputs with 1=male, 2=female and 3=unknown.

Individual data sets, which consisted of either a single array or combinations of arrays of harmonics were randomly divided into three sets; these were the training set (60%), test set (20%) and validation set (20%). The training set was used for model minimisation, the test set was used to determine when training was complete and the validation set was used as an unseen data set to evaluate the model. Results are presented for the validation sets. The original measurement data set (n = 599) was also randomly divided using the same techniques that were used for the neural network classification of harmonics. These results were used as a comparison for the results obtained using LDA, and from those obtained from the transect data.

The results from the neural network classification using the measurement data showed an overall correct classification of 0.84, 0.84 and 0.86 for the Alaskan, Nass and Skeena stocks, respectively. This was essentially the same result as the LDA analysis that showed an overall correct classification of 0.84 for the entire data set. The classification accuracy using harmonics was less than when using the measurement data and appeared to be variable depending on the choice of transects and whether length and sex were included (Table 1). In general, the addition of biological data increased classification rates. For instance, the highest classification rates achieved without biological data were from the Nass River (0.80); while the highest classification rates from the Nass River stock with the addition of biological data was 0.89. High classification rates for the Skeena River may be an artefact of unknown sex and subsequently requires further investigation.

This pilot study demonstrates the utility of neural networks for handling difficult classification problems and as a tool for developing new scale analysis approaches for stock separation. We found the method to be flexible: it did not require the explicit construction of algorithms to develop classification models and could be adapted readily to new datasets. In this study PNN was comparable to LDA when using same dataset and it allowed us to explore harmonics of the luminance profiles as a new dataset – one which could be obtained with a significant savings in labour. While the use of harmonics will require further investigation – such as using longer profiles to cover the first marine growth and combining it with measurement and sampling data – we believe it could lead to a more accurate and cost effective mechanism to determine stock relationships.

Equation 1. Discrete Fast Fourier transform used to transform the signal data from individual greyscale values from the time (*t*) domain to the frequency domain (*f*). Note return of complex number in the form of (a+b*i*).

$$H(f)=\sum_{t=0}^{n-1}h(t)\cos(2\pi ft)+i\sum_{t=0}^{n-1}h(t)\sin(2\pi ft)$$

Equation 2. Welch data window. Used to "pull" both ends of the luminance values close to zero.

$$w_i = 1-\left(\frac{1-0.5(n-1)}{0.5(n+1)}\right)^2$$

Equation 3. Inverse Discrete Fast Fourier transform used to transform the signal data from the frequency (*f*) domain to the time domain (*t*).

$$h(t)=\frac{1}{n}\sum_{f=0}^{n-1}H(f)\cos(2\pi ft)+i\frac{1}{n}\sum_{f=0}^{n-1}H(f)\sin(2\pi ft)$$

Equation 4. The power (harmonics) of the Fourier series was calculated as the absolute value |z| of the complex number.

$$|z| = \sqrt{a^2 + bi^2}$$

Fig. 3. Welch window function over the range 0–128.

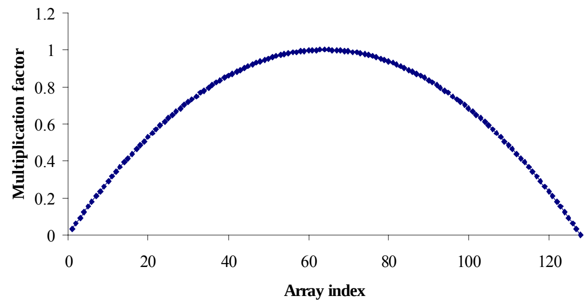


Fig. 4. Original Luminance profile after application of Welch window (blue series) with reconstructed profile using 21 complex numbers from the Fourier series (pink series) from T1 - AK0212U0001.

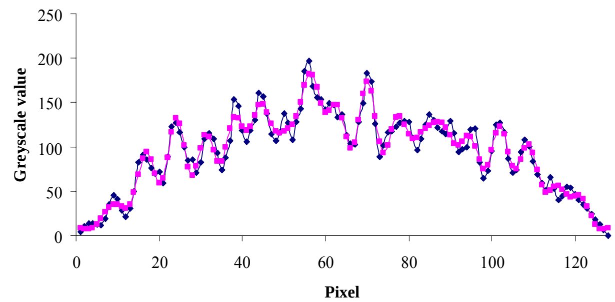


Fig. 5. Harmonics from T1 - AK0212U0001. The first 21 were used as inputs to the neural network.

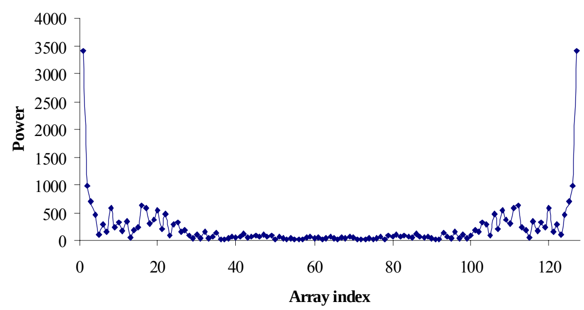


Table 1. Neural network inputs used for classification of scales for the three areas. Number of inputs in braces represent number of inputs including length and sex.

	Input	Number of inputs	Without Biological data			With length and sex		
			Alaska	Nass	Skeena	Alaska	Nass	Skeena
Single transects	Transect 1	21 (23)	0.6667	0.6098	0.3243	0.8333	0.7778	1
	Transect 2	21 (23)	0.2564	0.6341	0.2703	0.6389	0.8444	1
	Transect 3	21 (23)	0.2564	0.5122	0.4595	0.6667	0.8222	0.9722
	Transect 4	21 (23)	0.5385	0.4878	0.4595	0.8056	0.6667	1
	Transect 5	21 (23)	0.5128	0.5366	0.3784	0.6944	0.6667	0.9722
	Transect 6	21 (23)	0.2564	0.6341	0.2703	0.6111	0.8	1
Multiple Transects	Transect 1,6	42 (44)	0.4615	0.6098	0.2703	0.8333	0.8222	0.9444
	Transect 2,5	42 (44)	0.4872	0.6341	0.5676	0.6389	0.8222	0.9444
	Transect 3,4	42 (44)	0.4103	0.8049	0.3243	0.75	0.7778	1
	Transect 3,4,5	63 (65)	0.4103	0.8049	0.3243	0.5833	0.8444	0.9167
	Transect 1,2,3,4,5,6	126 (128)	0.5128	0.7561	0.2973	0.5833	0.8889	0.6944

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