Polynomial Regression Spectra Reconstruction of Arctic Charr's RGB

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Abstract. Arctic Charr (*Salvelinus alpinus L.*) exhibit red ornamentation at abdomen area during the mating season. The redness is caused by carotenoid components and it assumed to be related to the vitality, nutritional status, foraging ability and generally health of the fish. To assess the carotenoid amount, the spectral data is preferred but it is not always possible to measure it. Therefore, an RGB-to-spectra transform is needed. We test here polynomial regression model with different training sets to find good model especially for Arctic charr.

Keywords: Arctic Charr (*Salvelinus alpinus L.*), carotenoid, spectral data, sRGB to spectra transform.

1 Introduction

Arctic charr are an endangered fish species living in Finland [1]. It is also grown in fisheries and the individuals are considered valuable assets. The most striking feature of charr is its red abdomen area during the mating season. This red ornamentation is thought to be related to the ability of fish to acquire carotenoids from food since animals cannot synthesize carotenoid components (e.g. [2]). It is assumed to indicate the nutritional status and foraging ability.

Since the carotenoid component seems to be important factor for evaluating vitality, we are developing a system using spectral data for analyzing it. The survival of valuable fish in the quality evaluation is required but up until now, the spectral imaging is too slow, expensive, difficult and cumbersome to use for an ordinary layman. The relation between RGB and spectra has been studied in many papers; see e.g. Baronti et al., Bochko et al., Hardeberg, Heikkinen et al. [3-6]. The 2^{nd} and 3^{rd} order polynomial was chosen for this work.

The applying the transformation for the charr is a challenging task for many reasons. First, since the charr is a natural object, its coloration vary even within one individual. Then its surface and shape also set limitations. Of course, the camera and illumination need to be somehow characterized for the transformation. If the

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system is to be applied in fisheries and test places in nature, the number of test samples are limited.

In this paper, we describe tests with two polynomial regression models and training samples for obtaining the RGB-to-spectral transform dedicated for Arctic charr (see also [7]). The training samples consist of Macbeth chart and few pages from Munsell book. The spectral imaging is applied all the training and fish samples. The transform is calculated for sRGB presentation which is commonly used in many cameras. The sRGB is obtained from spectral data thus making the evaluation camera independent and the results can be thought to be optimal in this sense. To evaluate the quality of the transformation, we employed two commonly used error metrics: Root-Mean-Square error (RMSE) for spectra and ΔE of CIELab for human vision.

2 Spectral Reconstruction Methods for Arctic Charr

The spectral reconstruction for Arctic charr needs several stages as shown in Fig. 1. First, training set and polynomial are selected and this data is used for calculating the transformation matrix:

$$X \cdot W = Y, \tag{1}$$

where

X = RGB values of camera for the selected samples,
Y = spectral reflectance corresponding the samples, and
W = transformation matrix.

The transformation matrix is calculated in the least square sense using pseudo-inverse method. The obtained transformation matrix is then applied on the test set which consists of spectral images of charr. The quality of the reconstructed image is analyzed in two metrics: CIELab error ΔE for human vision,

$$\Delta E = \sqrt{(\mathrm{L} - \mathrm{L_t})^2 + (\mathrm{a} - \mathrm{a_t})^2 + (\mathrm{b} - \mathrm{b_t})^2}\ , \tag{2}$$

where

L,a,b = CIELab values for measured spectra, and
L_t,a_t,b_t = CIELab values for measured spectra
and root-mean-square error RMSE for the spectra

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(S(i) - \breve{S}(i)\right)^2}{n}}\ , \tag{3}$$

where

n=number of wavelengths,
S=original, measured spectra, and
Š=spectra approximation from transform.

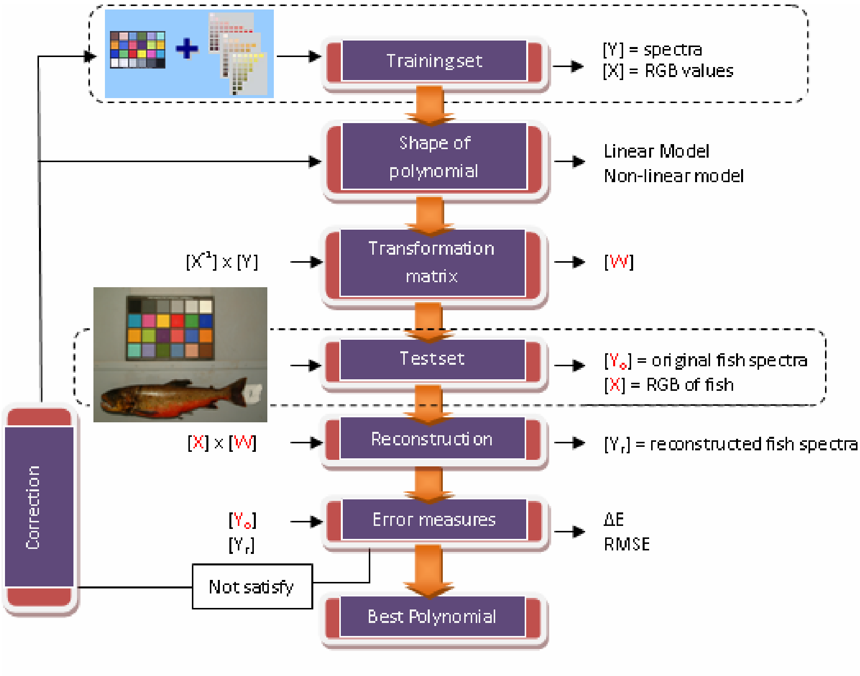

Fig. 1. Schema for spectral reconstruction

The best polynomial model is selected based on the error after the calculations. Table 1 shows terms of 2nd and 3rd polynomials which both have also a constant term (1st order polynomial was excluded due its simplicity).

Table 1. Terms of polynomials

Number of terms	Terms of polynomials
10	R G B R^2 G^2 B^2 RG RB GB 1
20	R G B R^2 G^2 B^2 RG RB GB RGB RGG RBB GRR GBB BRR BGG R^3 G^3 B^3 1

3 Reconstruction Results

Two different training sample set where used in reconstruction. All training and fish data was first subjected to spectral measurements. Then the corresponding sRGB presentation was calculated under illuminant 'D65' which is the ideal daylight 6500 K light.

3.1 Reconstruction with Macbeth Chart

The training set consisted of all 24 samples of Macbeth chart. The 2nd and 3rd order polynomials were applied to calculate the transform. Fig.2 shows an example of

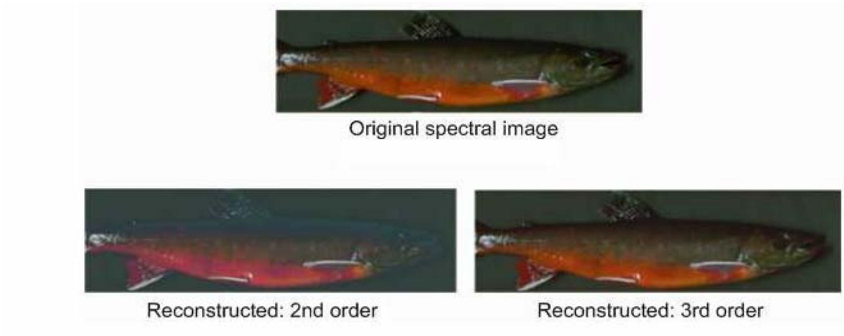

Fig. 2. The upper image is a sRGB presentation calculated from the original spectral image. The lower row display sRGB presentations computed from polynomial approximated spectra: left image is obtained using 2nd order transform, while the right image is from 3rd order approximation.

results: sRGB presentation for original spectra and spectra approximated from sRGB. The 2nd order approximation produces clearly color distortions for human point of view but color quality of 3rd order approximation is acceptable.

The numerical evaluation of data is presented in Table 2. The 3rd order polynomial transform produces smaller ΔE for the fish image than the 2nd order one but RMSE is bigger for the 3rd order. This indicates over fitting as shown in Fig. 3.

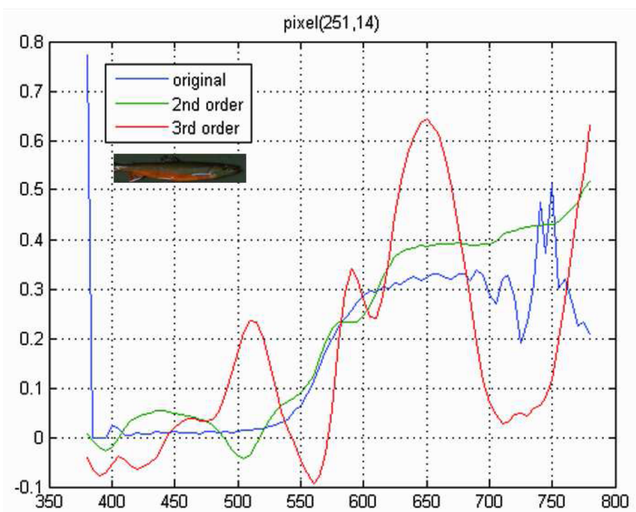

Fig. 3. The 3rd order polynomial transform over fits the spectra. Note that the original spectral data is noisy at the ends of the wavelength range.

Table 2. Numerical evaluation for Macbeth chart as a training set

Error metric		Average	Standard deviation	Maximum	Minimum
ΔE		Image of Fish			
	2nd	9.1862	6.9114	31.1366	0.1041
	3rd	2.8097	2.8057	27.2516	0.003
		Training set			
	2nd	0.7511	0.5437	1.9430	0.1354
	3rd	0.0551	0.0576	0.2244	0.0021
RMSE		Image of Fish			
	2nd	1.6078	2.2106	11.3326	0.1819
	3rd	3.186	3.5024	16.2798	0.2319
		Training set			
	2nd	0.0354	0.0250	0.1229	0.0094
	3rd	0.0262	0.0225	0.0916	0.0026

3.2 Reconstruction with Macbeth Chart and Pages from Munsell Book

To solve the problem of over fitting, the training samples were complemented with few pages from Munsell book. Munsell book is a colour atlas which has a large number of samples for different hues. The sample pages selected from the book (like YY or RR) have hues similar to the hues present in Arctic charr. Fig. 4 displays the sRGB presentations for the new training data. The extended training set clearly improves color quality for 2nd order model.

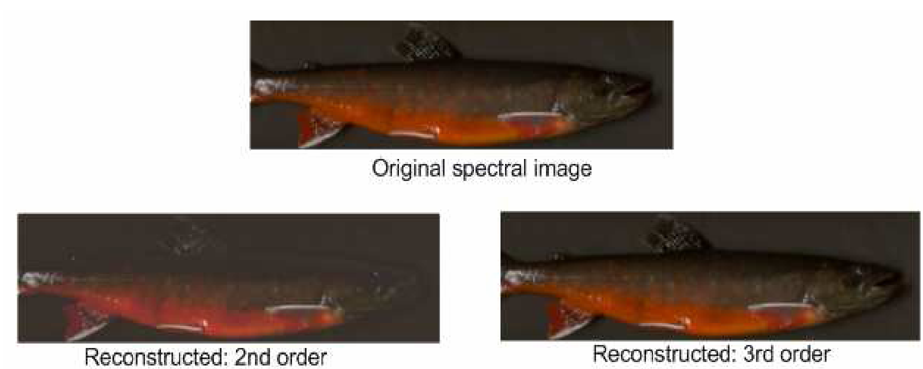

Fig. 4. Upper row: sRGB from measured spectra. Lower row: left image, sRGB from 2nd order transform and right image, sRGB from 3rd order transform. The extended training set clearly reduces the color distortion in the 2nd order polynomial transform.

Table 3 and 4 presents the numerical errors ΔE and RMSE obtained using different training set. The results indicate that the extending training set will reduce the average error in most of the cases, and that the 3rd order polynomial transform produces smaller errors. Tables 5 and 6 display the error calculated for skin patches of Arctic charr to test the transform with color variations. The results are the same also for these cases. The over fitting problem is also avoided as can be seen in Fig. 5.

Table 3. CIELab error

ΔE error **Polynomial**	Fish image	Average	Standard deviation	Maximum	Minimum
2nd	Macb	9.1862	6.9114	31.1366	0.1041
	Mac+XYY	7.7407	6.0777	28.2561	0.1058
	Mac+XYY+XYR	8.3574	6.4532	28.2481	0.0260
	Mac+YYRR(404)	8.2703	7.1867	31.8375	0.0360
3rd	Macb	2.8097	2.8057	27.2516	0.003
	Mac+XYY	3.0271	3.5854	26.9802	0.0147
	Mac+XYY+XYR	3.2334	3.1669	27.0605	0.0054
	Mac+YYRR(404)	1.8174	2.9300	27.1408	0.0030
	Training set				
2nd	Macb	0.7511	0.5437	1.9430	0.1354
	Mac+XYY	1.3823	1.8873	17.8670	0.0617
	Mac+XYY+XYR	1.0955	1.6314	18.0721	0.0821
	Mac+YYRR(404)	0.4700	0.5994	8.3434	0.0139
3rd	Macb	0.0551	0.0576	0.2244	0.0021
	Mac+XYY	0.6849	1.3344	13.2440	0.0233
	Mac+XYY+XYR	0.5458	1.0999	13.9019	0.0116
	Mac+YYRR(404)	0.0571	0.1188	2.2247	0.0016

Table 4. RMSE error for the extended training set

RMSE Polynomial	Training set	Average	Standard deviation	Maximum	Minimum
2nd	Macb	0.0354	0.0250	0.1229	0.0094
	Mac+XYY	0.0254	0.0168	0.1408	0.0032
	Mac+XYY+XYR	0.0276	0.0193	0.1554	0.0049
	Mac+YYRR	0.0188	0.0156	0.1620	0.0030
	Macb	0.0262	0.0225	0.0916	0.0026
3rd	Mac+XYY	0.0222	0.0159	0.1007	0.0023
	Mac+XYY+XYR	0.0240	0.0184	0.1456	0.0020
	Mac+YYR	0.0138	0.0139	0.1637	0.0016
	Fish Image				

Table 4. (*continued*)

2nd	Macb	1.6078	2.2106	11.3326	0.1819
	Mac+XYY	1.5047	2.2076	11.0383	0.2475
	Mac+XYY+XYR	1.4981	2.1945	11.0646	0.2938
	Mac+YYRR(404)	1.4041	1.9767	9.8274	0.1737
3rd	Macb	3.186	3.5024	16.2798	0.2319
	Mac+XYY	1.5418	2.3626	10.9252	0.1089
	Mac+XYY+XYR	1.4258	2.3840	10.9380	0.1255
	Mac+YYRR(404)	1.5349	2.1575	9.8115	0.0940

Table 5. Numerical evaluation of a sample

 Polynomial	ΔE	Average	Standard deviation	Maximum	Minimum
2nd	Macb	0.5867	0.3341	1.7043	0.0928
	Mac+YYRR	0.2449	0.1011	0.9747	0.0149
3rd	Macb	0.2009	0.0978	0.3766	0.0014
	Mac+YYRR	0.1534	0.0692	0.3573	0.0067
	RMSE				
2nd	Macb	0.3135	0.1812	0.7583	0.0636
	Mac+YYRR	0.469	0.3878	1.1527	0.0584
3rd	Macb	0.4224	0.5151	2.8739	0.063
	Mac+YYRR	0.4886	0.417	1.2334	0.0584

Table 6. Numerical evaluation of another sample

 Polynomial	ΔE	Average	Standard deviation	Maximum	Minimum
2nd	Macb	2.2833	2.2596	14.0901	0.0905
	Mac+YYRR	1.4028	1.2312	9.9955	0.42
3rd	Macb	0.3441	0.3428	4.1933	0.0023
	Mac+YYRR	0.445	0.2606	2.7709	0.0184
	RMSE				
2nd	Macb	0.3835	0.3063	1.6232	0.0738
	Mac+YYRR	0.2246	0.1044	0.5408	0.0629
3rd	Macb	0.7983	0.6225	2.1389	0.0518
	Mac+YYRR	0.296	0.1587	0.6033	0.0528

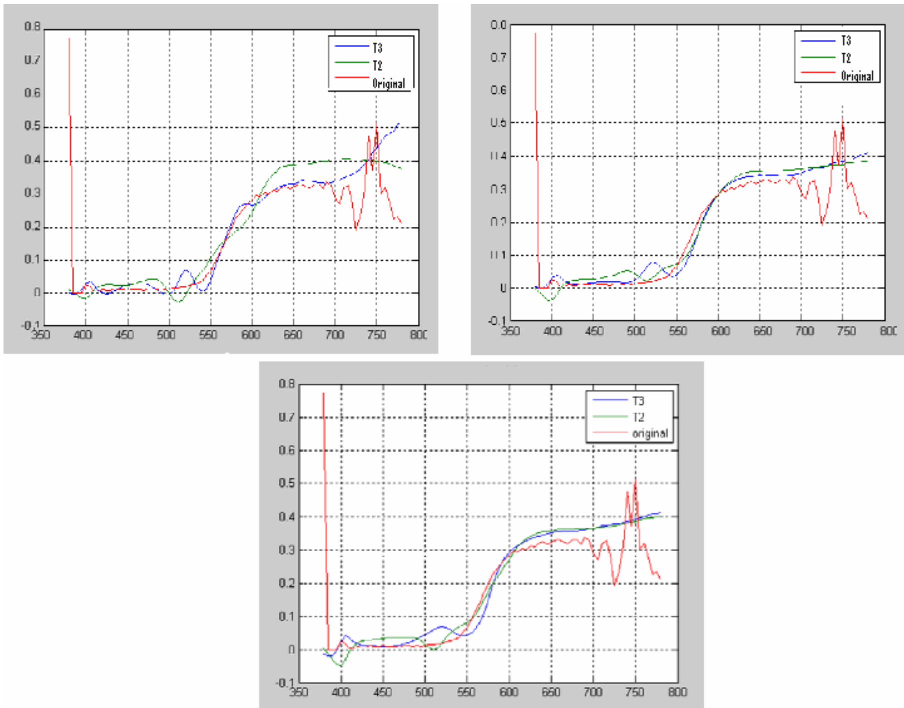

Fig. 5. The extended training set reduces the over fitting problem. Upper row, left image: training set Macbeth chart + Munsell YY; right image: Macbeth + Munsell YY and YR. The lower row, training set Macbeth chart + Munsell YY, YR and RR.

4 Conclusions

We have tested two polynomial regression models, 2nd and 3rd order polynomials, for sRGB-to-spectra transform with different training sets. The results indicate that a bare Macbeth chart will produce poor results both polynomials (color distortion and over fitting) when tested with Arctic charr. When adding more training samples from Munsell book corresponding to Arctic charr coloration, the models work better.

The obtained results clearly show that we can use RGB image to approximate the spectra for Arctic charr and thus make it as part of spectral based carotenoid content evaluation system.

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