Colorimetric characterization of negative film for digital cinema post-production

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Abstract

This paper aims to contribute to the colour management methods employed in the digital post–production of cinema images. It consists of building an accurate characterization model of the process of printing from a negative film to a positive. Several different generic methods were tested and their results analysed in order to assess their performance and gain more knowledge about their intrinsic nature, as well as that of the process itself. The neural network model outperformed the others. Its flexibility enabled it to achieve errors well below the variability of this process. It is the only one that can reach the very high quality required by the digital cinema industry. Colour copies of the figures and the VRML files may be found at the author's web page at *alexisgatt.free.fr / publications / negative.htm*.

Introduction

The spread of digital imaging technology over recent years has extended the limits presented to the artistic process of creation. However, from a colour science point of view, the movie industry also poses many new challenges. Indeed, transferring the process of film creation from analog to digital technology is a complicated task given the very high quality required, and already achievable by conventional means. The Computer Film Company (London, UK) and the Colour and Imaging Institute (Derby, UK) are therefore working jointly to establish a coherent colour control system for the digital post–production of film. A good introduction to the issues involved is provided by Lempp *et al*[1].

As a matter of fact, the proportion of digital technology used in cinema as a whole is still rather small compared to total movie output, but is likely to increase in coming years. One advantage of digital capture is that digital effects or editorial and artistic changes can be applied directly to the movie. On the other hand, the negative of a film captured using conventional methods first needs to be digitized before the post-production process can be initiated. However, the medium that will ultimately be distributed to local cinemas is a positive film. Therefore, regardless of whether the film was captured with digital or analog method, a negative master has to be printed, from which positive copies can be obtained and distributed widely. This process involves three colour imaging media, as can be seen from Figure 1: *negative film* which is what scenes are captured onto using photographic means, *positive film* which is made from the negative so as to have a rendering of the original scene that represents its colours and the *projection* of the positive film which results in the final rendering of the director's representation of a scene. Finally, the colour characteristics of each of these media can be described using different characteristics: negative and positive films can be described using different types of *densities*[2] (these are measurable properties that relate to the concentration of colorant in film) and the projection can be described in terms of the extent to which it stimulates the eye (e.g. CIEXYZ[3]) or in terms of its *appearance* in terms of lightness, chroma and hue (e.g. as predicted using a colour appearance model such as CIECAM97s[3]).

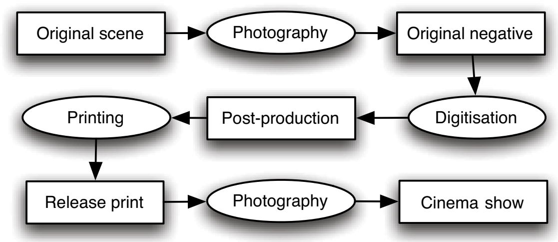

Figure 1: *Traditional film process chain, including digital post-production.*

In this context, the present study intends to establish an efficient control of the reproduction of colour in a hybrid imaging chain. The process starts with a silver halide colour negative film, involves digital processing among the intermediary steps, continues with the printing of another silver halide output medium, and ends with the projection of this medium onto a cinema screen . The parallel between digital post-production in cinematography and digital photofinishing of still photographs thus becomes evi-

	R channel		G channel		B channel	
	mean	max	mean	max	mean	max
Distance–weighted interpolation	0.06	0.21	0.06	0.21	0.08	0.26
Gaussian interpolation	0.07	0.26	0.04	0.26	0.04	0.18
Neural networks	0.02	0.05	0.02	0.07	0.02	0.13
Nonlinear model	0.11	0.34	0.15	0.53	0.17	0.55
Standard deviation of process	0.18		0.27		0.19	

Table 1: *Comparison of performance obtained by all the tested models. The results are expressed in terms of residuals of Status A densities.*

dent, as both fields start from a negative film to produce a positive as output medium. Whereas the latter has reached maturity as proven by the abundant literature available[4,5,6], little research has been devoted to the former, and knowledge in this field is mainly contained by small specialist companies.

The goal of this project thus consists of establishing a coherent colour management system for the development of a fully digital film process chain. Previous research performed as part of this project[1] has focussed on other areas of the considered imaging chain, and the present study aims to relate the properties of negative film to those of positive film at the printing process. Being able to do so will allow for the prediction of positive film characteristics given a piece of negative film, as well as the definition of the specifications required by negative films to achieve specific properties for positive film. This second function is particularly important for digital cinema post-production where the desired appearance of the projected film is known and a negative film needs to be produced to achieve it.

This study intends to achieve the above by means of developing mathematical models that can transform negative film densities to positive film densities and vice versa. Having such models is a key element of controlling the entire post–production process as they form an essential link between the negative and positive film media that are key to current distribution and presentation of motion pictures, irrespective of whether they were originated digitally or by analog means. Once the relationship between positive and negative film densities can be modeled accurately, all that will be needed is a model of the relationship between positive film densities and the appearance of its projection.

Characterisation models

Specifically, the aim is to develop a number of transforms between standardised spectral sensitivities related to printing densities for each of these types of film – Status A for positive and Status M for negative. Using real printing densities would have been more appropriate, since they are the densities that would be measured by a device having effective spectral responsivities equivalent to those of a particular print medium and a specific printer. Such information was unfortunately not available from the manufacturer of the medium, and thus standardised densities had to be used instead. The likely outcome is to significantly increase the complexity of the problem of modeling the system, since the densities used will not be representative of the exposure received by the individual layers of the print material, as will be discussed later. A large dataset of Status M inputs with their corresponding Status A outputs was collected to train and test the tested characterisation models. The problem therefore consisted of fitting a model to a curve highly correlated with the characteristic curve *D-Log E* of the process.

It was first attempted to characterise the process using an analytical approach. Indeed, the design of the mathematical model could benefit from knowledge of the inner architecture of the process. However, the necessary data being not available, the relative efficiency of several generic techniques was established by comparing them to each other, and also with classical methods which have been implemented previously. Several standard interpolation techniques have been tested, as well as non-linear programming method. Being part of mathematical programming algorithms, such methods can only form decision surfaces that are relatively simple, since they rely on the properties of continuous functions. On the other hand, heuristic search procedures, such as neural networks, are very good at exploring global and local optima. For instance, the neural network used in this article, a multi–layer feedforward perceptron[7], can implement decision surfaces of arbitrary complexity. An effective method to train this type of network is given by the generalized delta rule for learning by back–propagation[8]. The learning phase not only consists of finding the most appropriate architecture, i.e. the number of neurons in the hidden layer, but also the optimal learning rate and momentum. As learning rate is used to determine the speed at which the network learns, it may be thought that a high learning rate may speed up the process, and thus be more efficient. However this can cause problems. Indeed, as the adjustments made when the learning rate is high are also relatively high, weights may jump from one value close to the optimal one to another which is equally close, but in the *other* gradient direction. The network may thus end up oscillating around the optimal solution, but without actually reaching it. On the other hand, with a low learning rate, the network may be brought to a standstill in a local minimum and the global will again never be reached. Some techniques, such as simulated annealing, aim to solve these problems. The optimal configuration obtained from the learning phase contained a single hidden layer containing about 20 neurons, and the learning rate and momemtum were as low as 0.1.

Analysis of results

The efficiency of the model based on the neural network can be inferred unambiguously from Table 1. It clearly outperformed all the other models implemented. Indeed, the maxima of residuals in each channel are similar to the means obtained using the best interpolation method. Furthermore, the mean of the residuals is well below the standard deviation of the process itself. However, a more thorough analysis of the residuals is necessary for estimating the goodness of fit. Indeed, descriptive analysis methods focus on some key characteristics of a population and thereby compresses the available information into a few descriptive values. While they provide summaries of a population, they act as a narrow filter which may omit some meaningful characteristics, resulting in an incomplete analysis.

An alternative approach consists of displaying all the available data at the same time to find a more suitable *point of view*, i.e. one that gives a more meaningful visualisation of the data. The residuals' distribution was therefore represented in 3D using the VRML language[9]. For each observation in the testing set, a sphere was displayed at its exact density coordinates, and its colour was set according to the residual value at the considered point. However, although this 4D representation does not alter nor compress the characteristics of the residuals' population, it does not help either the analyst to find a meaningful point of view. Principal component analysis methods (PCA) might then be helpful. Indeed, they aim at constructing a subspace for the data that best preserves their dispersion and that allows for best discrimination among the data in a linear subspace of the original space. The first two axis of the obtained subspace will thus give valuable information about the distribution of the residuals in density space. Since the residuals' dispersion is much smaller than those of the Status M, more weight should thus be given to them by linearly transforming them before performing the PCA. The optimal discrimination plane was obtained by increasing the residuals' dispersion to twice that of the coordinates. Deducing the location of the residuals, and then the impact that has on the tested model, will be made much easier thanks to the PCA.

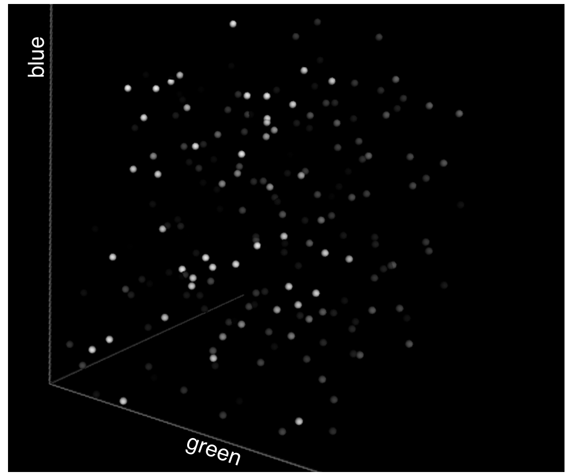

Figure 2: 4D representation of projection plane given by the PCA for the Gaussian interpolation. The shades of grey represent the magnitude of the residuals at that point.

For instance, the insufficiency of the functional part of the model based on the Gaussian interpolation can be inferred unambiguously from the PCA. The projection plane obtained for this model is shown in Figure 2, while Figure 3 indicates more precisely the location of this plane in density space. 74% of the total variation in the data set is accounted for by the two main axes of the PCA plane. The main vector corresponds to the first bisecting line of the density space. This conclusion is confirmed by a scatter plot of a Status M channel versus its corresponding Status A values, since a systematic pattern following the densities' magnitude is clearly present. However, the second axis was invisible from standard analysis methods. The residuals tend to be bigger when the point considered is located near the high green and blue densities, whereas it

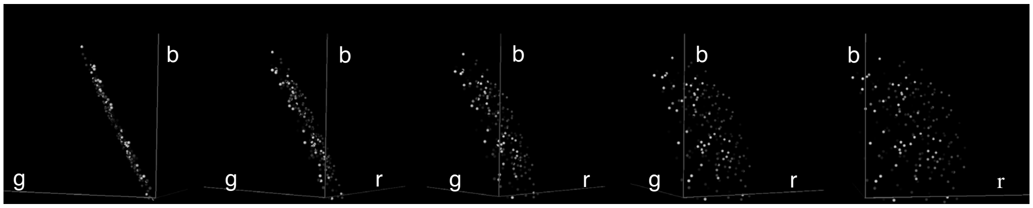

Figure 3: *Representation of the PCA plane under five consecutive angles (rotation of the density space around the blue axis).*

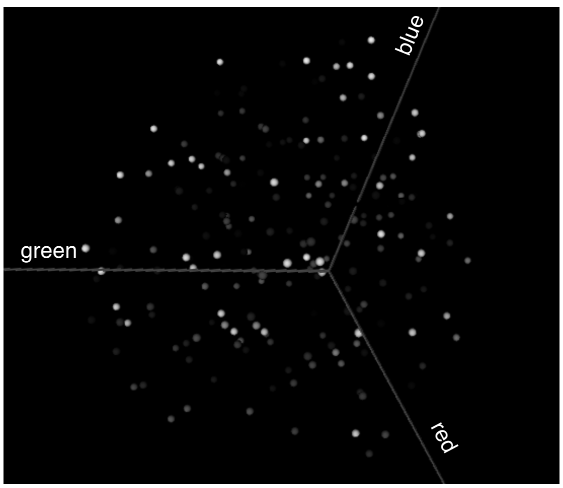

Figure 4: *4D representation of full data set viewed from the first bisecting line of the density space*

is the opposite when the coordinates of a point are close to high red densities. Figure 4, which shows a full 4D representation of the data, illustrates this point. Indeed, it can be noted that the green axis divides the data cloud into two distinct parts, with blacker spheres (i.e., smaller residuals) near the red axis, and whiter spheres in the other part of the space. Since residuals are not randomly distributed, this functional part of this model is not sufficiently accurate. On the other hand, no specific structure appeared from the PCA analysis for the model based on the neural network, confirming the excellence of the results achieved by this model. It is thus safe to conclude that it constitutes a very good approximation of the considered process. In this case, the PCA was demonstrably helpful as an efficient way to accurately identify the trend in the residuals distribution.

Discussion

Table 1 shows the intrinsic standard deviation of the negative film printing process, which was obtained from the measured data used in this study. They express typical variations of the negative film printing process and therefore put the magnitudes of model prediction residuals into context. Given the quality of the results achieved by the neural network, it might be concluded that the process is highly nonlinear, since neural networks are considered to be highly nonlinear techniques. However, if that were so, better performance would also be expected from the nonlinear model.

It was previously mentioned that the choice of densities was not optimal for modelling this specific process. It is likely that the real spectral sensitivities of the print material are not the same as the Status M or A spectral sensitivities. Therefore, the amount of exposure received by the individual layers of the print material will not be directly equal to the corresponding Status M or A densities. It will more probably depend on a mixture of them. These interactions, known as cross-talk effects (overlapping spectral characteristics and chemical inter-image effects), constitute the main reason explaining the diverse results of every model. Indeed, the models based on the interpolation techniques and the nonlinear programming method did not take into account all the input channels when estimating outputs, but only one. On the other hand, the large number of degrees of freedom incorporated in the neural network model gave it the flexibility required to take such phenomenon into account. Indeed, whether cross–talk occurs can be demonstrated by proof by contradiction using the neural network model. This model provides an excellent estimation of the process' behaviour and each Status A output is estimated from all the three Status M inputs. Any cross–talk occurring in the print process will thus be reflected by the network. Say the hypothesis that cross–talk does not occur is made. Therefore, the results for a given channel should not be affected by the values in the other channels. A forward pass was performed in the network after setting to nil

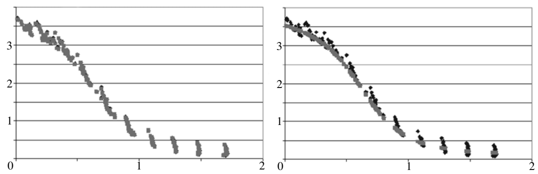

Figure 5: *Results of network tested under normal conditions (left) and with nil values (right). On the left figure, the predictions overlap perfectly the observed outputs.*

the values of two defined channels, and the predictions for the third were observed. Figure 5 shows the predictions of the network for the red channel relative to the values of the corresponding input channel. The results under normal conditions are shown on the left and those with nil values on the right. Similar results were obtained for the other channels.

In order to achieve the results previously presented, the network takes into account the values of all input channels, which proves that the hypothesis previously stated is wrong. Therefore, it is confirmed that cross–talk occurs during the print process, which explains the poor performance obtained by the other models. In order to provide an approximation of a channel's outputs, most of the information required by a model is contained in the corresponding channel's inputs. But for the estimation to be accurate, information from all the input channels are a *sine qua non* condition. The neural network model thus offers a more flexible solution that the other models. The good results it achieved show that it can adjust its parameters more freely and more efficiently to a wider range of conditions. It might be possible to include cross-talk phenomenon into the other models by incorporating matrices to account for the fact that Status A and M are a mixture of the real printing densities of the medium. Nevertheless, all the tested techniques are affected by the weakness inherent in generic models as their validity is restricted to the set of observations used to derive them. This is a concern especially from the point of view of the data set's colour gamut in that the predictions of generic model's for colours outside the training set are unfounded.

Conclusion

This paper aimed to contribute to the colour management methods employed in the digital post–production of cinema images. Specifically, it consisted of developing an accurate characterization model of the process of printing a negative film to a positive. Several different generic methods were tested and their results analysed in order to assess their performance and gain more knowledge about their intrinsic nature, as well as that of the process itself. A detailed understanding of the process' characteristics emerged from this analysis. It is clear that the model based on the neural network outperformed the others. The results obtained with it were excellent since it did not suffer from any of the problems previously mentioned. Its flexibility enabled it to achieve errors well below the variability of this process. It is the only one that can reach the very high quality required by the digital cinema industry.

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Biography

Alexis Gatt received an engineer degree in Artificial Vision from Saint-Etienne University, France in 2000 and a MSc degree in Colour Imaging from the Colour Imaging Institute, UK in 2001. He also worked in several companies as an image processing specialist for three years. He is currently studying towards a PhD in Digital Colour Reproduction at the Colour Imaging Institute.