Transforming an analytically defined color space to match psychophysically gained color distances

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ABSTRACT

In this paper a new method for defining a transformation between a source color space and a more perceptual uniform color space will be presented. The main idea is to use a three dimensional Free-Form Deformation to deform a source color space in such a way, that the new distances between chosen color samples match psychophysically estimated data as close as possible. This deformation of space is controlled via a set of control points being placed on a three dimensional grid. The essential task of finding suitable control point coordinates in the destination color space has been solved with an Evolution Strategy.

Keywords: color space transformation, perceptual uniform color spaces, evolution strategies, free-form deformations

1. INTRODUCTION

For the definition of a perceptual uniform color space two main problems have to be solved. The first one is the quantification of perceived color distances and the second one is to find a transformation from a well known color space e.g. 1976 CIELUV to a new one which matches the psychophysically estimated distance values as close as possible.

Measuring color distances can range from measuring distances, which are close to just noticeable differences up to quantifying distances between e.g. samples evenly distributed over the gamut of a monitor. Furthermore, there are a great variety of psychophysical methods which can be used for the respective purpose. The data, which we used for this work will briefly be described in section 1.2, but the applicability of this work is not restricted to this kind of data. What we need is information about ideal distances between a discrete number of samples, but it does neither matter if the samples are close to each other or not nor if they are evenly distributed or not. Moreover the ideal distance values can come form psychophysical experiments or from other sources. Examples will be given in Section 4.

Section 1.2 will describe one possible way of finding a transformation from a source color space to a new one based on psychophysically estimated data.

Considering the drawbacks of the first approach a new method for defining such a transformation has been developed. The main idea is to use a three dimensional *Free-Form Deformation (FFD)* to deform a source color space in such a way, that the new distances between the chosen color samples match the psychophysically gained distance values as close as possible. This deformation of space is controlled via a set of control points which are placed on a regular grid in the source color space.

The essential problem of finding suitable control point coordinates in the destination color space under consideration of the above mentioned goals is a very complex optimization task. We have solved it with the help of an *Evolution Strategy (ES).*

Implementation details and results for an artificial data set as well as for data from psychophysically experiments will be presented in section 4 and 5.

1.1 MEASURING PERCEIVED COLOR DISTANCES

Various methods for examining human color perception and measuring perceived distances between a set of color samples are discussed in e.g.[5,9,13,23,25]. In particular[23] describes our recent work in this field. Two psychophysical methods which we have used shall briefly be summarized:

For both cases 35 colors evenly distributed in an extended version of the CIELUV color space[15] were chosen as representatives of the actual monitor gamut.

Direct Magnitude Estimation (DME): Using a calibrated monitor and a well defined environment all possible combinations of two out of 35 given color samples (=595 pairs) were shown. Test candidates had to assign distance values to each color pair according to the perceived color distances. The results of the DME method are ratio scale values. Details to this standard method can be found in[5, 9, 23].

Method of Triads (MT): Color triples were shown, and test candidates had to decide which two colors were most similar and which two colors were most different. Ordinal scale values can be derived from these data by counting total numbers of similarity and dissimilarity decisions for each possible color pair, see[5, 9, 23]. Because of the high number of possible color triples (6545) and the missing uncertainties concerning the decision of the candidates, only the more critical half of them were evaluated by test candidates. The other triples, for which the decisions of the candidates were “known” in advance, were evaluated by comparing distances according to the extended CIELUV color space, see [23].

While DME seems to be better for determining global trends, MT gives more accurate results for local tendencies. Therefore a combination of these data seems to be appropriate.

1.2 FINDING A TRANSFORMATION

One method used for defining a transformation from a known source color space *S* to a new more uniform color space works as follows [23, 24]:

The first step is to arrange all color samples in *N* in such a way that the empirically measured distances between the samples are matched as closely as possible. In statistical data analysis, *Multidimensional Scaling* [5, 8, 24] is a well known term for this kind of optimization problems. After finding an arrangement of the color samples, a general transformation from the known color space *S* to the new space *N* is possible with the help of a tri-linear interpolation.

Unfortunately, this approach has several drawbacks: 1) To make a tri-linear interpolation possible , the samples must lie on a uniform tree-dimensional cuboid grid in *S*. 2) In general, this transformation is not continuous in its first derivative between cuboids. 3) Piecewise linear interpolation is only a poor interpolation technique. More color samples with much more empirically measured data would be necessary to increase accuracy. 4) Colors from any color space other than *S* must first be transformed to *S* before the transformation to *N* can take place.

2. USING A FREE-FORM DEFORMATION (FFD) FOR THE TRANSFORMATION

About a decade ago an efficient and intuitive method for designing three dimensional objects called *Free-Form Deformation (FFD)* was introduced by Barr[4] and has been improved ever since [21, 11, 6, 7, 16]. Originally it was thought of a method for sculpturing solid models and for representing them. The general idea behind this approach is to embed an initial model into a deformable region of space specified by a regular lattice with a discrete number of control points. Each point of the model has a unique parameterization which defines its position within the lattice. By deforming the 3D lattice the original model is deformed as well, see *Fig.1*. The new position of points of the model can be recalculated with the help of the original parameters and the new positions of the control points, see *Eq.1*. Thus all kinds of rather complex shaped models can be generated in an easy, elegant, and intuitive way.

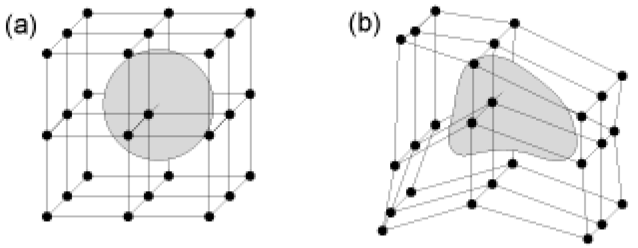

Fig. 1 Free-Form Deformation: (a) control points of the initial lattice and (b) displaced control points of the final lattice.

From the mathematical point of view, the FFD involves a transformation from R^3 to R^3 defined e.g. in terms of a trivariate tensor product Bernstein polynomial, which can be seen as a natural extension of Bezier curves to three dimensions [21].

Based on the new control point positions $\vec{C}_{i,j,k}$ (i = 0..u, j = 0..v, k = 0.. w), an arbitrary point p=(r,s,t) (r,s,t $\in$ [0,1]) will be transformed as follows:

$$FFD(\vec{p}) = \sum_{i=0}^{u} \sum_{j=0}^{v} \sum_{k=0}^{w} \vec{C}_{i,j,k} B_i^u(r) B_j^v(s) B_k^w(t) \qquad (1)$$

with $B_\alpha^\beta(\gamma)$ being the Bernstein polynomial:

$$B_\alpha^\beta(\gamma) = \binom{\beta}{\alpha} \gamma^\alpha (1-\gamma)^{\beta-\alpha} \qquad (2)$$

The advantages of FFDs are that they can be applied to CSG based solid models as well as to models bounded by different analytical surfaces. Furthermore, the can either be used for the whole model or only for a certain part of it without losing derivative continuity to any degree. Moreover two or more FFDs can be applied in a piecewise manner resulting in more complex deformations than could be achieved with a single FFD. The Bezier curves‘ convex hull property and the variation diminishing property, which signalize high quality (smoothness, numerical stability, ..), can also be applied to the FFD. The disadvantage of the FFD is that it is a global deformation method which is not suitable for complex, subtle local deformations necessary e.g. for modeling facial expressions.

Since 1990 the range of possible applications of FFDs has further been increased. Griessmair and Purgathofer[11] e.g. use a trivariate B-Spline representation and Coquillart[6] introduced Extended Free-Form Deformations (EFFD) which use combinations of lattices instead of one originally proposed parallelepiped lattice. This extension allows a greater inventory of deformable spaces, but loses some of the flexibility and stability of the approach of Sederberg and Parry [21]. MacCracken [16] allows arbitrary shaped deformation lattices by successively refining a 3D lattice into a sequence of lattices that converge uniformly to a region of 3D space. This technique allows a grater variety of deformable regions and thus a broader range of shape deformations. Another trend is to use FFDs for soft object animation, see e.g. [7].

Thus a great variety of FFDs are available and can be used for a lot of different purposes, like the design of complex objects (e.g. turbine blades or airplane wings) or animation. In any case, using FFDs requires the specification of new positions of control points of a 3D lattice. This can either be achieved by interactively moving the control points until the resulting bended, twisted, or tapered object fulfills the esthetic requirements of the designer or by moving the control points with analytical functions where the designer only specifies certain parameters. In some cases such positions for the control points have to be found that certain difficult constraints will be fulfilled or a given quality function is maximized. *Evolution Strategies (ESs)*, a special form of Evolutionary Algorithms, offer an interesting stochastical optimization approach, in particular because of the possibility to use arbitrary constraints and /or evaluation functions.

3. USING EVOLUTION STRATEGIES FOR THE SPECIFICATION OF THE FFD

Finding suitable control point positions $\vec{C}_{i,j,k}$ of the final lattice of a FFD to match given constraints as good as possible or to maximize a given quality function is in general a very complex optimization task. No efficient deterministic algorithm is known which finds the global optimum or a good approximation within a reasonable amount of time.

In the past Evolutionary Algorithms, which mimic the search process of natural evolution in a simplified way, have shown their suitability to solve various difficult optimization problems. These algorithms are based on the collective learning process within a population of individuals, each of which represents a search point in the space of potential solutions to a given problem. For a general introduction, see [1, 2, 3, 10, 17]. Especially Evolution Strategies (ESS) have proven to be a very robust and efficient method for optimizing complex multimodal numerical functions, see [1,2,3,10,18].

procedure (μ,λ) - ES
$t \leftarrow 0$;
initialize (P_0);
evaluate (P_0);
while not terminate (P_t) **do**
    /* use μ parents to create λ children */
    $R_t \leftarrow$ recombine (P_t);
    $M_t \leftarrow$ mutate (R_t);
    evaluate (M_t);
    $P_{t+1} \leftarrow$ select (M_t);
    $t \leftarrow t+1$;
done

Fig. 2. Pseudo code of a (μ,λ) - ES..

In Fig. 2 the pseudo code of a (μ,λ)-ES which we propose for optimizing the FFD's control point positions is shown. An individual is represented by a vector $\vec{I}$ consisting of n scalar values, namely all coordinates of the control points $\vec{C}_{i,j,k}$. In total, there are therefore $n = 3(u+1)(v+1)(w+1)$ coordinate values subject to optimization.

In contrast to the traditional random initialization of the starting population (as described in [1, 2, 3]), a starting population P_0 consisting of μ individuals is generated by mutating the original control point coordinates of the undeformed state. This gives more or less meaningful starting solutions, improving convergence speed and reducing problems with the recombination of nearly equivalent but mirrored or rotated solutions substantially. Each newly generated individual is then evaluated by a problem specific fitness function $f(\vec{I})$ which gives in general higher values for better solutions. The initial population P_0 evolves over generations towards better and better regions of the search space by means of randomized processes of recombination, mutation, and selection. A discrete recombination is used to generate λ new individuals inheriting values from parental solutions randomly chosen by P_t. This newly generated individuals will then be mutated.

After mutation the best μ individuals are selected out of the λ new offsprings to be the parents P_{t+1} for the next generation. This process is continued until a certain termination condition is fulfilled, e.g. an individual with satisfactory fitness is found or the individuals do not improve within a given number of generations.

The fitness functions, which we used to deform a source color space in such a way, that the new distances between the chosen color samples match the psychophysically gained distance values as close as possible are the following:

Let $\Delta_{a,b}$ be the mean values of the pschyphysically gained distance values between the chosen color samples, $\delta_{a,b}$ the Euclidean distance between these samples transformed according to solution I, and g the number of color samples used. The following function $f_1(I)$, which should be minimized, is particularly useful for finding a solution for the DME test data:

$$f_1(\vec{I}) = \sum_{a=1}^{g-1} \sum_{b=a+1}^{g} \left(\delta_{a,b} - \Delta_{a,b}\right)$$

(3)

In different DME data series, distances between two color samples will generally not be the same. Some values will vary more, others less. Therefore it seems necessary to consider standard deviations of mean distances $\Delta_{a,b}$ for multiple DME data series to get a more meaningful function. We refer to this extended objective function by $f_{1,\kappa}$. Details are given in [19].

For MT data the following function $f_2(I)$ is more appropriate:

$$f_2(\vec{I}) = \sum_{a=1}^{g-2} \sum_{b=a+1}^{g-1} \sum_{c=b+1}^{g} \# - MT - mismatches$$

(4)

The number of MT data mismatches is counted for all possible color triples of samples. A “mismatch” means that the two nearest (or most distant) samples of each triple of the individual I are not the same as in the answers from the MT test. To consider differences between more than one MT measurement series, only mismatches against a color pair which was selected in at least a given percentage (e.g. 75%) of all measurement series as nearest or most distant pair should be counted. We refer to this extended objective function by $f_{2,\eta}$.

4. IMPLEMENTATION AND RESULTS FOR AN ARTIFICIAL DATA SET

Our implementation is based on a modified version of ESCAaPaDE [12] 1.2, which is a freely available software environment for doing experiments with ES. A 4x4x4 FFD control point grid proved to be the best choice when our DME and MT data based on g = 35 color samples were used. In this case the number of control points ($4^3 = 64$) is just higher than the number of color samples, which means that the FFD is potentially flexible enough to independently transform each color sample to any position. Using a 4x4x4 grid results in n = 192 parameters which have to be optimized.

Real, psychophysically determined DME and MT data contain variances, errors and inconsistencies. The best possible values for f_1 and f_2 are therefore not known and it cannot be estimated in a quantitative way how good a resulting solution is. Solutions can only be compared to each other and checked on colorimetric plausibility. To measure the abilities and accuracy of the new approach without having to struggle with these problems, we determined FFD based transformations form RGB space to the CIELUV space for the actually used monitor. For this purpose artificial DME and artificial MT test data were calculated from CIELUV ΔE values between the 35 color samples. When using these exact test data a globally optimal solution is known to have objective function values $f1_{opt} = f2_{opt} = 0$.

Our tests resulted in solutions near the global optimum. Table I and Fig.3. give some information about the final best solutions of 30 test runs using the fitness function f1 together with DME data in the first case and the fitness function f2 together with DME data in the second case. 3000 generations (=3 x 10^5 evaluated individuals) were performed per run.

(a) $f_1(I)$		(b) $f_2(I)$	
$f_1(I) <= 0.001$:	4 (13%)	$f_2(I) <= 10$:	12 (40%)
$f_1(I) <= 0.01$:	26 (87%)	$f_2(I) <= 20$:	24 (80%)
$f_1(I) <= 0.1$:	28 (93%)	$f_2(I) <= 50$:	28 (93%)

Table 1:Numbers of test runs with final solutions better than given quality levels when using (a) f1(I) or (b) f2(I) as objective function for the ES.

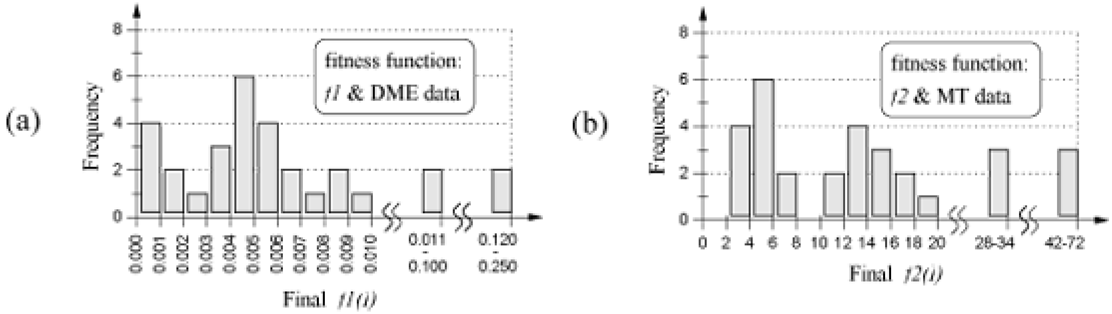

Fig. 3. Histograms of final best objective function values from 30 independent test runs when using (a) f1 or (b) f2 as objective functions for the ES.

For test case (a) 26 runs (87%) succeeded in finding a solution with f1(I) <=0.01. Only four runs had much higher objective values (f1(I) > 0.001). Fig. 4a shows the average best f1-values per generation calculated out of the 26 runs with f1(I) <= 0.01. Our implementation needed approximately 165 minutes of CPU time for a single run on a HP-9000/705 workstation.

For test case (b) 24 runs out of 30 (80%) succeeded in finding a solution with f2(I) <=20. See figure 4b for average best f2-values per generation calculated out of these 24 most successful runs. The implementation needed about 470 minutes of CPU time for a single run. Runs for test case (a) were faster because f1 can be calculated in much less time. See [19] for more details on the implementation and results.

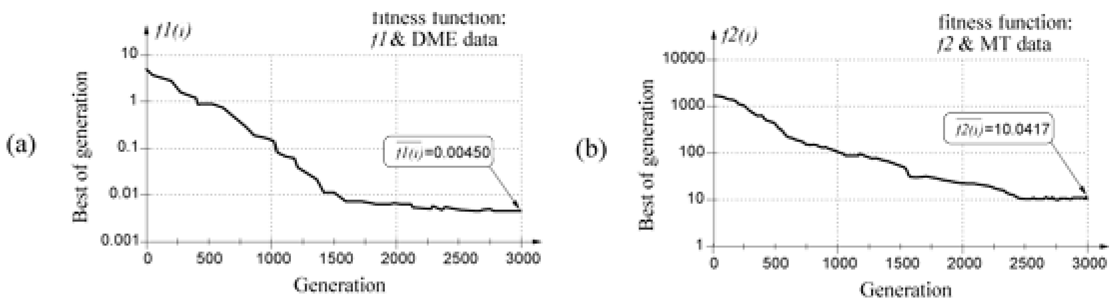

Fig. 4. Average best objective function values plotted over generation: (a) for the 26 runs using f1 which converged to solutions with f1(I) <= 0.01, and (b) for the 24 runs using f2 which converged to solutions with f2(I) <=20..

5. TRANSFORMING A SOURCE COLOR SPACE TO MATCH PSYCHOPHYSICALLY GAINED DISTANCES

The previously described test cases for finding a transformation to a known color space like CIELUV using artificially determined DME and MT data have shown the general suitability of the new ES/FFD approach.

As both kinds of psychophysical experiments (especially MT) are very time consuming we currently have only a small number of data series available (DME: 5 MT:4 from three different persons). The differences between these runs are not very large, but there are definitely more runs needed to derive accurate and "objective" results.

When using the above mentioned DME and MT data, the best f1 and f2 values lie clearly above 0 because of the already mentioned empirical errors and data inconsistencies. When using $f_{1,\kappa}$, 12 of 30 ES runs found solutions with $f_{1,\kappa} = 0$ within 3000 generations. When using $f_{2,\eta}$ (η= 75%) the best observed solution was $f_{2,\eta}$=36. In general our solutions determined by $f_{1,\kappa}$ or $f_{2,\eta}$ do not differ substantially and show distortions comparable to the ones which occur between the original 1976 CIELUV color space and the extended version of the CIELUV space developed by Kokoschka [15].

The results were also compared to the results gained by multidimensional scaling. Most of the FFD solutions had better objective values, especially when f_1 and f_2 were used for evaluation. See [19, 23] for more details.

6. CONCLUSION

Using a free-form deformation in combination with evolution strategies finding suitable control point coordinates, seems to be a very promising new approach to transform a source color space in such a way, that psychophysically estimated data or data from other sources are matched as close as possible. The results of our experiments are very encouraging.

The greatest advantage of the new FFD/ES approach all in all are the good approximation properties of FFD (e.g. the derivative continuity to any degree) and the large flexibility (e.g. fitness functions can be adapted to the respective psychophysical data and to the goals which shall be achieved; the color samples may have arbitrary positions in the source color space).

This approach starts with a source color space and "ideal distance values" between a discrete number of samples and comes up with a new color space and with a function to transform any possible color of the source color space into the destination space.

The advantages and possibilities of the FFD/ES approach have already also been used for other tasks in the field of color science, like the colorimetric characterization of a scanner [26].

7. ACKNOWLEDGEMENTS

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