A Scanner Based Neuro-Fuzzy Technique for Color Evaluation of Textile Fabrics

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ABSTRACT

The most significant objective of this paper is to bring to light the relationship between the scanner device-dependent color space and the device independent CIE color space. The scanner characterization was done based on neuro-fuzzy techniques. To show the usefulness of the proposed method, we performed some simulations. The experimental results are very promising. It should be noted that the new method outperforms the previous methods such as polynomial regression and neural network techniques.

KEYWORDS

Scanner, Evaluation, Fabric, Textile, Color, Neuro-Fuzzy.

1. INTRODUCTION

A color space is a method by which we can specify, create, and visualize color. Different color spaces are better for different applications. A device independent color space is one where a set of parameters will produce the same color on whatever equipment they are used. The CIE XYZ (1931) system is at the root of all colorimetry. It is defined such that all visible colors can be defined using only positive values, and, the Y value is luminance. A device dependent color space is a color space where the color produced depends on both the parameters used and on the equipment used for display [1-2].

Due to the increase of low-cost color devices (digital color cameras, scanners, printers etc.) during the last few years, color calibration has become an important issue. Such devices should truly reproduce color images, but experience shows they do not. Among the main reasons, we note the diversity of acquisition, display, and printing technologies, which make standardization difficult. Each device has a different gamut, i.e., a different set of colors that it can acquire or reproduce. Furthermore, the characteristics of the devices often vary with time. Hence, a calibration procedure is unavoidable for high quality color reproduction. Each device has its own color space defined by the relationship between the input colors and the corresponding *RGB* codes used to represent them. Consequently, waiving device calibration, which converts the native color space into a standard device-independent one, will often result in unmatched colors throughout the system. Moreover, images acquired with different devices cannot be reliably compared and stored. In some cases, experimental results might not be reproduced with different digitizing equipment. A simple method of converting scanner *RGB* responses to estimates of object tristimulus *XYZ* coordinates is to apply a linear transformation to the RGB values. The transformation parameters are selected subject to minimization of some significant error measure. While the linear method is easy, it can be quite imprecise. Linear methods are only guaranteed to work when the scanner sensor responsivities are within a linear transformation of the human color-matching functions. The basic idea of color target-based characterization is to use a reference target that contains a certain number of color samples. These colors are scanned by scanner, and then measured by a spectrophotometer to obtain the *RGB* values and their corresponding *XYZ* values. Typical methods like three-dimensional lookup tables with interpolation and extrapolation, least squares polynomial modeling and neural networks can used to derive a transformation between scanner RGB values and *XYZ* values [3-12].

Shams and Amirshahi [11, 12] characterized scanner by polynomial regression and neural network method. In polynomial method, the first proposed method consisting of applying a non-linear correction to the scanner RGB values followed by polynomial regression function directly to CIELAB color space yields mean values of color difference of calibration and testing as 2.4 and 3.8 ΔE^*ab, respectively. In neural network method, the best result obtained by neural network with 3 hidden layers which have respectively 3, 9, 3 nods. In the best method the average color difference for training and testing patches respectively was 2.04 and 4.35 ΔE^*ab.

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2. The Adaptive Neuro-Fuzzy Inference System (ANFIS)

The fuzzy inference system (FIS) is a popular computing framework based on the concepts of fuzzy set theory, fuzzy IF/THEN rule and fuzzy reasoning to transform an input space into an output space. Here is a list of general observations about fuzzy logic:

•Fuzzy logic is conceptually easy to understand: The mathematical concepts behind fuzzy reasoning are very simple. What makes fuzzy nice is the "naturalness" of its approach and not its far-reaching complexity.

•Fuzzy logic is flexible: With any given system, it is easy to massage it or layer more functionality on top of it without starting again from scratch.

•Fuzzy logic is tolerant of imprecise data: Everything is imprecise if you look closely enough, but more than that, most things are imprecise even on careful inspection. Fuzzy reasoning builds this understanding into the process rather than tacking it onto the end.

•Fuzzy logic can model nonlinear functions of arbitrary complexity: You can create a fuzzy system to match any set of input-output data. This process is made particularly easy by adaptive techniques like ANFIS (Adaptive Neuro-Fuzzy Inference Systems), which are available in the Fuzzy Logic Toolbox.

•Fuzzy logic can be built on top of the experience of experts: In direct contrast to neural networks, which take training data and generate opaque, impenetrable models, fuzzy logic lets you rely on the experience of people who already understand your system.

•Fuzzy logic can be blended with conventional control techniques: Fuzzy systems do not necessarily replace conventional control methods. In many cases fuzzy systems augment them and simplify their implementation.

•Fuzzy logic is based on natural language: The basis for fuzzy logic is the basis for human communication. This observation underpins many of the other statements about fuzzy logic.

The last statement is perhaps the most important one and deserves more discussion. Natural language, which is used by ordinary people on a daily basis, has been shaped by thousands of years of human history to be convenient and efficient. Sentences written in ordinary language represent a triumph of efficient communication. We are generally unaware of this because ordinary language is, of course, something we use every day. Since fuzzy logic is built atop the structures of qualitative description used in everyday language, fuzzy logic is easy to use.

The basic structure of fuzzy inference system consists of three conceptual components:

A rule base, as database or dictionary, which defines the membership functions used in the fuzzy rules, and reasoning mechanism, which performs the inference procedure upon the rule and a given condition to derive a reasonable output or conclusion.

A fuzzy system can be created to match any set of input/output data. This can be done with an adaptive neuro-fuzzy inference system (ANFIS). ANFIS is about taking a fuzzy inference system and training it with a backpropagation algorithm, well known in the artificial neural network (ANN) theory, based on some collection of input/output data [13-16].

ANFIS consists of a Takagi Sugeno FIS and has five layers as shown in Figure 1. The first hidden layer is for fuzzification of the input and T-norm operators are positioned in the second hidden layer to compute the rule antecedent part. The third hidden layer normalizes the rule strengths followed by the fourth hidden layer where the resultant parameters of the rule are determined. Output layer computes the overall input as the summation of all incoming signals. ANFIS uses backpropagation learning algorithm to determine premise parameters (to learn the parameters related to membership functions) and least mean square estimation to determine the consequent parameters. A step in the learning procedure has two parts: In the first part, the input data are propagated, and the best consequent parameters are estimated by an iterative least mean square method, while the premise parameters are assumed to be fixed for the current cycle during the training set. In the second part, the patterns are propagated again, and in this epoch, backpropagation is used to modify the argument parameters, while the resulting parameters remain fixed. This method is then repeated. The fuzzy inference system is known by numerous other names, such as fuzzy-rule-based system, fuzzy expert system, fuzzy model, fuzzy associative memory, fuzzy logic controller and simply fuzzy system [17-19].

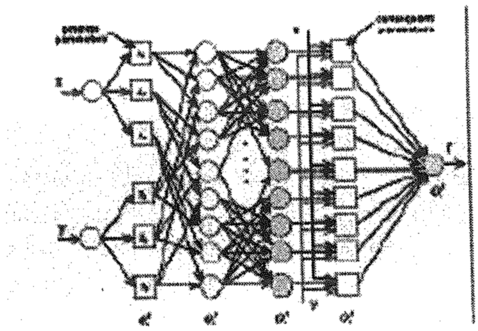

Figure 1. Structure of ANFIS.

3. MATERILA AND METHODS

The Benq 5550T color scanner was used for scanning. The fabrics scanned under the condition of 600 pixels/inch and 24 bit /pixel. The colorimetric data of dyed fabrics were measured by using Texflash spectrophotometer of Datacolor Corporation under condition of 2-degree standard observer and D65 illuminant source. The colored fabrics were prepared by dyeing Polyester fabrics with disperse dyestuff in varieties of colors. The chromaticity of fabrics is shown in Figure 2. A set of 141 patches of fabric were used as training set and 26 patches of dyed fabrics were kept for testing. All computations were performed by using MATLAB software.

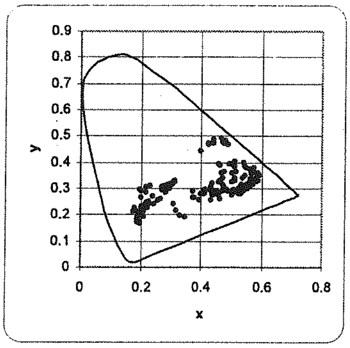

Figure 2. Chromaticity istribution of colored fabrics.

Neuro-Fuzzy Method: In this work, some methods for the colorimetric characterization of color scanners are proposed. The goal of our characterization is to establish the relationship between the device dependent color space of scanner and the device independent CIEXYZ and CIELAB color space. For evaluation and comparison of these different methods, the mean color difference between the calculated and measured CIELAB values of each patch was calculated as:

$$\Delta E*ab = \sqrt{(\Delta L*)^2 + (\Delta a*)^2 + (\Delta b*)^2} \quad (1)$$

where $\Delta L*$ is the different between actual and predicted $L*$ (lightness), $\Delta a*$ is the different between actual and predicted a* (redness/greenness) and $\Delta b*$ is the different between actual and predicted $b*$ (yellowness/blueness).

The experimental procedure in a neuro-fuzzy method is outlined as follows:

1. Take an image from each fabric by scanner and obtain the corresponding scanner *RGB* responses.
2. Measure the CIEXYZ and CIELAB values of fabrics by spectrophotometer.
3. Run neuro-fuzzy training that matches RGB of fabrics to their CIE specification by hybrid method (Figure (2)).

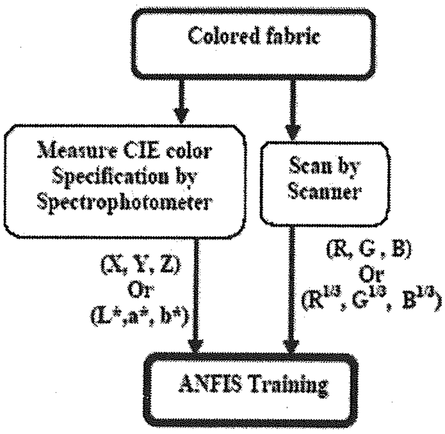

Figure 2. Neuro-fuzzy training.

1. Transform scanner RGB to CIE color space by the trained neuro-fuzzy.
2. Calculate the individual color difference for each patch and find the mean value of them for each model (Figure 3).

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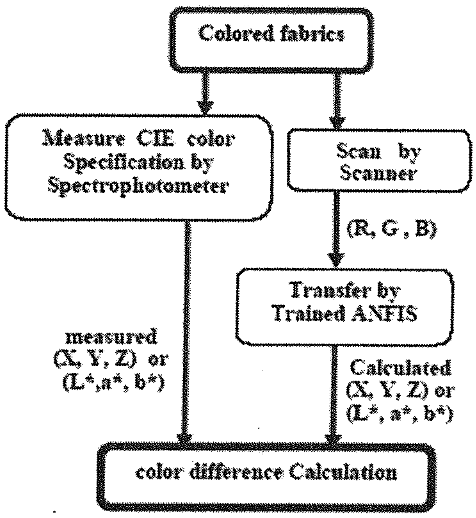

Figure 3. Neuro-fuzzy testing.

The various models of neuro-fuzzy, which was used in this works are shown in Table 1. For evaluation and comparing of these different methods, the mean color difference between calculated and measured CIELAB values of each patch has been calculated by Equation 1.

TABLE 1. THE TOPOLOGY OF NEURO-FUZZY.

No. of model	Number of membership functions			Membership functions
	Input 1	Input 2	Input 3	
1	3	2	3	gbellmf
2	3	2	3	gauss2mf
3	3	2	3	gaussmf
4	3	2	3	psigmf
5	2	2	3	gbellmf
6	2	2	3	gauss2mf
7	2	2	3	gaussmf
8	2	2	3	psigmf
9	2	2	2	gbellmf
10	2	2	2	gauss2mf
11	2	2	2	gaussmf
12	2	2	2	psigmf
13	2	3	2	gbellmf
14	2	3	2	gauss2mf
15	2	3	2	gaussmf
16	2	3	2	psigmf
17	3	3	3	gbellmf
18	3	3	3	gauss2mf
19	3	3	3	gaussmf
20	3	3	3	psigmf
21	3	2	2	gbellmf
22	3	2	2	gauss2mf
23	3	2	2	gaussmf
24	3	2	2	psigmf
25	3	3	2	gbellmf
26	3	3	2	gauss2mf
27	3	3	2	gaussmf
28	3	3	2	psigmf
29	2	3	3	gbellmf
30	2	3	3	gauss2mf
31	2	3	3	gaussmf
32	2	3	3	psigmf

Results and Discussion

In this work, neuro-fuzzy has been used for transform RGB to CIEXYZ and CIELAB color spaces. The results of simulation are shown in Tables 2 to 9 as color difference between measured and calculated value of colorimetric specification of each fabric.

Neuro-fuzzy for CIEXYZ: In this method, three ANFIS systems were used. Each system has three input nods referred to the scanner RGB values and one output referred to one of three parameters of the three stimulus (X, Y, Z) of colored fabric. Several membership functions such as gbellmf (Generalized bell-shaped built-in membership function), gauss2mf (Gaussian combination membership function), gaussmf (Gaussian curve built-in membership function) and psigmf (Built-in membership function composed of the product of two sigmoidally-shaped membership functions) have been used for input nodes. Different numbers of membership functions were also used for each input nodes as shown in Table 1. The neuro-fuzzy system has been trained by a hybrid method consisting of back propagation for the parameters associated with the input membership functions, and the least squares estimation for the parameters associated with the output membership functions. After training, the system was tested for all samples and the color difference value between measured and predicted CIEXYZ color coordinates calculated according to Equation 1 are summarized in Tables 2 and 3. In these tables, Mean, Max, Min and Std, respectively, are the average, maximum, minimum and standard deviation of color difference.

TABLE 2. COLOR DIFFERENCE VALUE OBTAINED BY APPLYING NEURO-FUZZY TO CIEXYZ (TRAINING SAMPLES).

No. of model	Mean	Max	Min	Std
1	2.128	15.537	0.043	2.470
2	2.066	13.881	0.010	2.199
3	2.377	14.254	0.046	2.251
4	2.657	16.456	0.028	2.480
5	3.119	27.331	0.018	3.129
6	2.570	16.030	0.089	2.375
7	3.148	17.082	0.087	2.672
8	2.994	15.795	0.027	2.757
9	2.593	17.801	0.247	2.548
10	2.608	17.502	0.119	2.473
11	2.730	18.233	0.205	2.472
12	3.776	17.420	0.230	3.028
13	2.579	17.149	0.068	2.485
14	2.339	26.292	0.011	3.076
15	2.470	18.019	0.121	2.468
16	2.449	18.048	0.161	2.568
17	1.754	11.650	0.009	1.872
18	1.930	25.372	0.003	3.324
19	1.634	10.660	0.004	1.645
20	1.696	12.049	0.008	1.964
21	1.848	15.538	0.006	2.428
22	2.125	15.286	0.001	2.489
23	2.041	18.399	0.017	2.555
24	2.123	15.601	0.013	2.517
25	3.932	16.122	0.255	2.216
26	2.085	7.986	0.040	1.560
27	2.863	9.190	0.174	1.829
28	2.507	7.599	0.105	1.602
29	3.246	17.797	0.104	2.663
30	3.053	10.703	0.046	1.982
31	4.182	20.167	0.165	3.240
32	3.157	10.903	0.042	2.328

TABLE 3. COLOR DIFFERENCE VALUE OBTAINED BY APPLYING NEURO-FUZZY TO CIEXYZ (TESTING SAMPLES).

No. of model	Mean	Max	Min	Std
1	7.042	57.803	0.627	19.291
2	12.396	160.639	0.407	38.861
3	15.616	98.536	0.434	26.400
4	20.257	246.780	1.032	66.737
5	5.699	33.213	0.618	9.063
6	7.237	51.094	0.757	11.023
7	12.128	195.393	0.928	38.695
8	9.220	61.878	0.761	13.481
9	4.780	32.396	0.850	6.068
10	5.435	32.836	0.911	7.766
11	4.994	31.936	0.464	6.022
12	7.199	33.119	1.513	7.093
13	6.139	32.655	0.435	7.579
14	9.815	114.561	0.427	59.318
15	10.255	51.389	0.443	14.622
16	12.772	189.933	0.434	47.243
17	7.244	58.657	0.384	12.560
18	17.891	158.946	0.681	67.734
19	10.382	95.045	0.672	19.513
20	16.679	275.237	0.623	79.700
21	9.088	1.054	0.826	25.297
22	10.183	24.766	0.757	40.679
23	10.771	51.553	0.676	86.280
24	11.746	138.318	1.019	77.847
25	26.608	72.483	1.368	75.074
26	20.596	217.421	0.976	72.459
27	11.146	53.956	0.510	25.196
28	13.848	19.815	0.987	39.504
29	27.073	237.135	0.660	68.242
30	27.337	230.249	0.914	54.140
31	14.372	22.549	1.877	86.339
32	15.393	154.242	0.972	30.100

Based on Tables 2 and 3, the best results obtain by 17^{th} model with three gbellmf membership functions for each input(*R, G, B*). The average color differences of this model were 2.61, 1.74 and 7.24, respectively, for total, training and testing samples.

In the next step, three ANFIS systems were developed. Each system has three input nods referred to cubic root of RGB values and one output referred to one of three parameter of the three stimulus (*X, Y, Z*) of colored fabric. After training, the system was tested for all samples and the results are summarized in Tables 4 and 5.

TABLE 4. COLOR DIFFERENCE VALUE OBTAINED BY APPLYING NEURO-FUZZY TO CIEXYZ (CUBIC ROOT OF RGB ($R^{1/3}, G^{1/3}, B^{1/3}$)) (TRAINING SAMPLES).

No. of model	Mean	Max	Min	Std
1	2.291	17.281	0.156	2.528
2	2.007	16.702	0.070	2.386
3	2.129	16.246	0.079	2.446
4	3.034	16.819	0.275	2.929
5	2.602	17.940	0.462	2.472
6	2.712	18.130	0.097	2.569
7	2.836	17.669	0.208	2.564
8	2.777	17.247	0.244	2.458
9	2.901	18.841	0.418	2.693
10	3.410	18.369	0.128	2.588
11	3.174	18.798	0.277	3.012
12	4.452	22.966	0.402	3.485
13	2.582	18.407	0.025	2.567
14	2.621	18.369	0.045	2.497
15	2.833	18.193	0.210	2.534
16	2.973	17.401	0.300	2.460
17	2.041	15.249	0.097	2.357
18	2.193	15.050	0.043	2.189
19	2.205	14.431	0.032	2.336
20	2.501	14.043	0.014	2.330
21	2.793	18.165	0.097	2.639
22	2.411	18.412	0.162	2.469
23	2.619	17.162	0.293	2.414
24	3.804	17.369	0.151	2.940
25	2.092	17.496	0.039	2.471
26	1.926	18.086	0.019	2.518
27	2.484	17.104	0.031	2.399
28	2.587	18.826	0.047	2.491
29	2.460	16.118	0.038	2.477
30	2.604	20.043	0.096	2.784
31	2.590	21.170	0.043	2.757
32	2.697	16.251	0.117	2.626

Based on Tables 4 and 5, the best results obtain by 19^{th} model with three gaussmf membership functions for each input(*R, G, B*). The average color difference of this model was 2.55, 2.205 and 4.406 respectively for total, training and testing samples.

Neuro-Fuzzy for CIELAB: In the second neuro-fuzzy method, three ANFIS systems have been used. Each system has three input nods referred to the scanner RGB values and one output referred to one of three parameter of the CIELAB color coordinates (L^*, a^*, b^*) of colored fabric. Several membership function such as gbellmf (Generalized bell-shaped built-in membership function), gauss2mf (Gaussian combination membership function), gaussmf (Gaussian curve built-in membership function) and psigmf (Built-in membership function composed of the product of two sigmoidally-shaped membership functions) was used for input nodes. Also, different number of membership function was used for each input nod.

TABLE 5. COLOR DIFFERENCE VALUE OBTAINED BY APPLYING NEURO-FUZZY TO CIEXYZ (CUBIC ROOT OF RGB $(R^{1/3}, G^{1/3}, B^{1/3})$) (TESTING SAMPLES).

No. of model	Mean	Max	Min	Std
1	12.057	119.796	0.406	28.038
2	7.181	16.174	0.377	22.569
3	6.086	33.319	0.634	9.865
4	12.233	72.791	0.557	20.808
5	6.306	7.845	0.518	13.246
6	8.877	14.003	0.531	21.527
7	7.061	18.879	1.046	15.688
8	6.732	14.697	0.603	13.794
9	6.653	3.341	0.624	21.044
10	6.691	6.867	0.527	24.025
11	5.630	31.552	0.668	6.010
12	8.626	5.447	0.194	20.623
13	6.037	4.823	0.798	19.964
14	6.421	5.352	0.655	23.874
15	5.680	11.720	0.411	15.712
16	7.841	14.365	0.298	16.543
17	7.997	75.557	0.583	17.434
18	8.426	112.952	0.260	29.500
19	4.406	33.132	0.510	6.408
20	11.888	140.721	0.335	64.260
21	7.917	2.782	0.616	20.888
22	6.859	5.134	0.498	24.459
23	7.099	31.933	0.342	12.996
24	10.546	41.864	0.905	10.245
25	7.175	9.812	0.465	18.906
26	7.105	7.873	0.605	24.220
27	12.871	59.298	0.924	19.797
28	11.943	19.115	1.562	16.776
29	7.685	9.460	0.566	18.548
30	10.435	60.207	0.404	71.196
31	12.555	142.331	0.887	55.684
32	10.221	52.312	1.209	19.934

The ANFIS was trained by hybrid method consisting of backpropagation for the parameters associated with the input membership functions, and least squares estimation for the parameters associated with the output membership functions. After training, the ANFIS was tested with all samples and the color difference value between measured and predicted CIELAB color coordinates was calculated according to Equation 1 and results are summarized in Tables 6 and 7. In next step, three ANFIS system were used. Each system has three input nods referred to cubic root of RGB and one output referred to one of three parameters of the CIELAB color coordinates (L^*, a^*, b^*) of colored fabric. After training, the system was tested for all samples and the results are summarized in Tables 8 and 9.

TABLE 6. COLOR DIFFERENCE VALUE OBTAINED BY APPLYING NEURO-FUZZY TO CIELAB (TRAINING SAMPLES).

No. of model	Mean	Max	Min	Std
1	1.576	12.722	0.045	2.279
2	1.631	14.675	0.008	2.315
3	1.539	12.947	0.066	1.957
4	1.449	14.764	0.034	2.300
5	2.034	14.252	0.117	2.276
6	1.909	14.722	0.059	2.406
7	1.959	14.704	0.041	1.992
8	2.146	12.104	0.060	2.200
9	2.073	17.916	0.106	2.510
10	2.132	17.057	0.059	2.407
11	2.160	18.409	0.139	2.488
12	1.676	18.740	0.083	2.406
13	1.968	16.077	0.048	2.422
14	1.826	17.002	0.018	2.340
15	2.009	16.145	0.188	2.352
16	1.941	17.449	0.008	2.399
17	1.343	12.398	0.010	1.969
18	1.231	12.921	0.005	2.108
19	1.203	12.789	0.011	1.483
20	1.378	12.866	0.002	1.981
21	1.837	12.442	0.152	2.110
22	1.830	14.119	0.029	2.076
23	1.748	13.924	0.052	2.259
24	1.883	16.691	0.036	2.433
25	1.575	12.057	0.015	2.106
26	1.424	13.860	0.011	2.008
27	1.521	13.200	0.031	2.150
28	1.588	13.654	0.001	2.114
29	1.575	13.320	0.052	1.981
30	1.577	13.720	0.006	2.261
31	1.669	14.535	0.072	1.966
32	1.629	12.660	0.005	2.108

TABLE 7. COLOR DIFFERENCE VALUE OBTAINED BY APPLYING NEURO-FUZZY TO CIELAB (TESTING SAMPLES).

No. of model	Mean	Max	Min	Std
1	5.033	33.623	0.713	7.235
2	6.910	70.657	0.532	14.772
3	7.478	89.760	0.210	18.394
4	9.874	130.121	0.561	25.891
5	4.800	32.622	0.571	7.754
6	4.637	31.135	0.372	6.201
7	4.695	32.718	0.554	7.628
8	5.683	37.775	0.478	9.027
9	4.067	31.348	0.807	6.095
10	4.162	31.818	0.545	6.326
11	4.126	31.954	0.765	6.341
12	7.184	67.056	0.911	14.165
13	5.498	33.071	0.647	8.510
14	9.515	130.667	0.844	26.057
15	6.797	73.162	0.544	15.133
16	4.941	32.683	0.401	6.980
17	20.373	136.450	0.358	38.858
18	8.805	56.297	0.461	13.330
19	24.911	206.306	0.600	47.351
20	10.545	48.632	0.680	14.455
21	5.667	34.447	0.839	9.508
22	6.531	48.585	0.434	12.140
23	3.726	33.918	0.638	6.647
24	4.712	32.480	0.527	7.041
25	6.751	46.829	0.405	10.957
26	5.662	33.018	0.461	8.633
27	6.596	33.866	0.455	9.371
28	8.930	106.932	0.446	21.504
29	4.739	32.954	0.589	6.929
30	5.570	32.825	0.217	8.019
31	7.317	87.492	0.477	17.913
32	8.335	94.601	0.478	19.142

Based on Tables 6 and 7, the best results obtain by 23th model with 3, 2 and 2 gaussmf membership functions, respectively, for *R, G* and *B*. The average color difference of this model was 2.056, 1.748 and 3.726, respectively, for total, training and testing samples.

TABLE 8. COLOR DIFFERENCE VALUE OBTAINED BY APPLYING NEURO-FUZZY TO CIELAB (CUBIC ROOT OF RGB ($R^{1/3}, G^{1/3}, B^{1/3}$)) (TRAINING SAMPLES).

No. of model	Mean	Max	Min	Std
1	1.681	17.260	0.038	2.428
2	1.639	17.092	0.062	2.381
3	1.711	15.582	0.056	2.295
4	1.902	16.706	0.054	2.416
5	2.052	17.625	0.026	2.497
6	1.935	17.480	0.029	2.464
7	2.087	18.485	0.075	2.421
8	2.158	18.176	0.094	2.529
9	2.122	18.637	0.203	2.528
10	2.251	17.874	0.218	2.509
11	2.286	18.958	0.108	2.482
12	2.092	17.630	0.234	2.380
13	2.036	18.179	0.102	2.506
14	2.035	17.760	0.031	2.462
15	2.082	17.994	0.059	2.490
16	2.077	18.123	0.084	2.513
17	1.377	14.371	0.012	2.267
18	1.368	14.723	0.006	1.832
19	1.347	14.145	0.016	2.264
20	1.388	16.375	0.013	2.365
21	1.956	19.347	0.246	2.453
22	1.944	17.891	0.006	2.554
23	1.992	19.699	0.172	2.463
24	2.296	17.754	0.061	2.594
25	1.594	14.523	0.034	2.339
26	1.616	17.775	0.028	2.499
27	1.657	15.598	0.041	2.344
28	1.874	17.397	0.032	2.569
29	1.737	15.092	0.073	2.352
30	1.707	15.516	0.116	2.131
31	1.816	15.185	0.088	2.287
32	1.738	15.835	0.058	2.412

TABLE 9. COLOR DIFFERENCE VALUE OBTAINED BY APPLYING NEURO-FUZZY TO CIELAB (CUBIC ROOT OF RGB ($R^{1/3}, G^{1/3}, B^{1/3}$)) (TESTING SAMPLES).

No. of model	Mean	Max	Min	Std
1	4.819	32.737	0.373	6.784
2	8.788	51.259	0.466	13.267
3	6.046	33.913	0.284	8.364
4	7.828	36.013	0.675	9.276
5	5.264	32.299	0.521	7.798
6	6.899	64.356	0.518	13.800
7	9.783	137.759	0.677	27.410
8	5.206	33.268	0.354	7.536
9	4.332	32.069	0.720	6.379
10	5.182	32.636	0.578	8.147
11	4.693	32.126	0.586	6.604
12	6.524	36.900	0.795	9.413
13	5.245	32.408	0.553	7.031
14	8.011	66.546	0.673	14.669
15	5.106	32.269	0.661	7.083
16	5.487	32.494	0.512	7.466
17	7.086	42.108	0.378	11.103
18	24.236	428.265	0.503	84.921
19	7.492	57.553	0.563	12.585
20	8.352	45.443	0.723	11.452
21	4.176	32.333	0.379	7.099
22	4.729	32.426	0.362	7.432
23	4.932	33.122	0.657	8.604
24	6.174	32.542	0.290	8.206
25	5.581	33.312	0.316	7.684
26	5.936	32.460	0.406	7.896
27	6.114	33.210	0.402	9.406
28	7.911	32.610	0.424	9.268
29	7.771	64.431	0.492	14.620
30	27.266	514.830	0.543	102.162
31	6.485	34.090	0.658	9.363
32	8.449	50.451	0.155	12.009

As shown in Tables 8 and 9, the best results were obtain by the first model with 3, 2 and 3 gbellmf membership functions, respectively, for $R^{1/3}$, $G^{1/3}$ and $B^{1/3}$. The average color difference of this model was 2.17, 1.681 and 4.819, respectively, for total, training and testing samples.

Further information of the effect of membership functions is provided in Figure 2. The results in this figure show that the effect of membership functions depends on types of models.

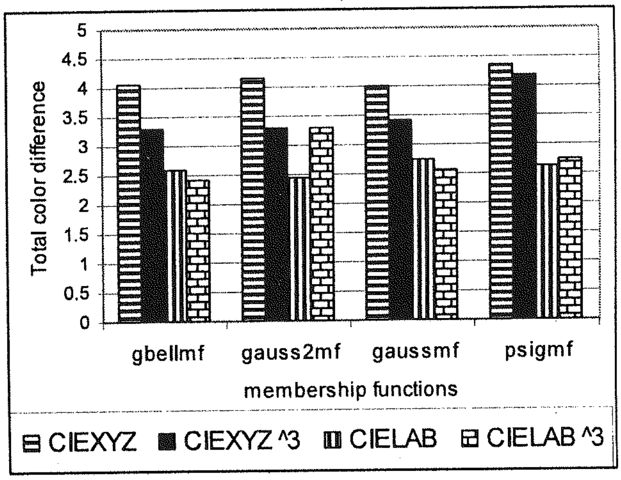

Figure 2. The effects of membership functions.

The results of best model for each method are summarized in Figure 3. The best result is obtained by applying neuro-fuzzy to CIELAB color coordinates (L^*, a^*, b^*) and the scanner RGB values. The color difference of the best method are 1.748, 3.726 and 2.056, respectively, for total, training and testing samples.

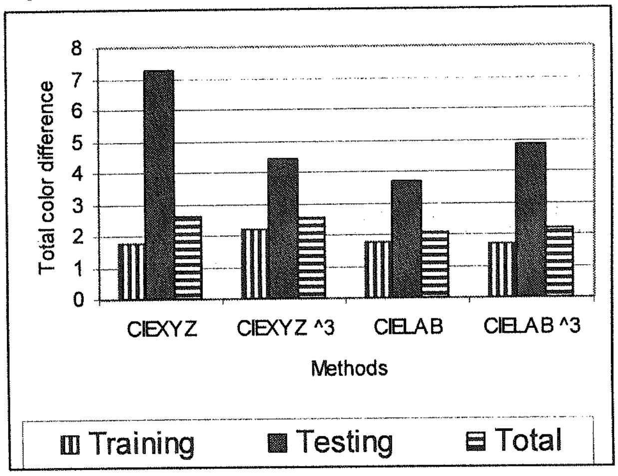

Figure 2. The results of best model for each method.

4. CONCLUSION

In this work, it was tried to establish a relationship between the device-dependent color space of a scanner and the device-independent CIE color space by using neuro-fuzzy technique. Several membership functions such as gbellmf, gauss2mf, gaussmf and psigmf were used for input nodes. Also, different numbers of membership function were also tested for each input node. The systems were trained by a hybrid method. After training, each neuro-fuzzy system was tested with all data set and the color difference between measured and predicted CIELAB color coordinates was calculated for linear and nonlinear RGB values. The best neuro-fuzzy method has three input with 2, 3, 3 gbelmf membership function. In the best condition, the mean values of color difference of training, testing and all patches respectively were 1.748, 3.726 and 2.056. The best prediction was obtained by neuro-fuzzy architecture with the CIELAB color coordinates. The accuracy of this method is comparable with neural network and polynomial regression [11, 12].

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