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Statistical Modelling of a Colour Naming Space

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Abstract

In this paper, we deal with the colour naming visual task in computer vision. Our goal is to develop a colour naming model to be included in a real surveillance application, where images have to be automatically annotated with people clothes description, for a further content-based image browsing.

Although colour naming has been a usual goal in psychophysical research, it is a quite novel topic in computer vision. Colour naming is posed as a fuzzy set problem where each colour category is presented as a fuzzy set with a characteristic function. Our goal is to find a model which provides membership values as similar as possible to the values that would give a real observer.

To this end, we propose a Sigmoid-Gaussian model as the membership function of the colour fuzzy categories. We analyse its properties and results to confirm the suitability of this model versus most common Gaussian models. To test the results, we have developed a colour naming experiment that has provided a set of membership values for a set of colour samples. Although the data used is far from being a complete learning set, it has been a first step to evaluate the proposed model.

Introduction

The work presented in this paper is framed in a large surveillance application that is being developed. The aim of this application is the retrieval of personal information from a database where the identification data of people is jointly stored with their appearance description. The appearance description is automatically inserted by the system from an image taken when the person is standing up in front of the reception desk. The application is designed to work in highly restricted access buildings where people must give their identification at the entrance. Since the security staff will make retrieval queries, the appearance descriptions have to be stored in terms of natural language, such as 'dark hair', 'red tie' or 'blue shirt'. This work is concerned with the description of the clothes colour; therefore, the colour naming problem is the main topic of our research.

The frame presented above implies that our colour naming module has to act just as a human observer would do. Hence, two constraints have to be considered on this approach. Firstly, it has to present colour constancy abilities since the system has to give a stable output under normal changing conditions of any hall of a building. This will take us to some considerations about the colour space to use. Secondly, the colour naming learning set has to take into account colour judgements of the system users. In this sense, we will present a preliminary experiment we have done to collect psychophysical data. Finally, we estimate the parameters of a Sigmoid-Gaussian function that will model colour membership and will allow giving a complete colour description of any image region. Before going deeply in these three steps we will review basic ideas on colour naming.

Colour Naming

In this work, colour naming problem is posed as a fuzzy-based approach. Kay and McDaniel[1] were the first in proposing a formulation of colour categories as fuzzy sets that provide a useful framework for the colour naming problem.

According to fuzzy set theory, any colour category C is characterised by a function f_C which assigns to each colour sample x a value $f_C(x)$ within the [0,1] interval. This value represents the degree of membership of x to colour term C. From this point of view, the goal of any colour naming method will be the definition of a membership function for each colour category.

In this paper, we will model the membership functions derived from psychophysical data collected with an experiment we will present in a section below. The set of stimulus used is acquired by our system, and we will model the membership functions for a device-dependent colour space.

At this point, the main question to be answered is about which is the function that can better model the colour categories. Previous research on statistical modelling of colour data has been focused on Gaussian models[2]. An interesting approach for colour naming going in this direction was proposed by Lammens[3], who used a symmetric Gaussian model. In that case, the fitting process is done over the categories of the Munsell colour space considering the boundaries and focuses for each category defined by Berlin and Kay[4] for the English language. This process is based on a minimization that fits the Gaussian function constrained to get maximum values for those points in the category focus, a certain threshold value for those points in the category boundary and a minimum value for those points in other categories.

Considering these previous steps and towards to get useful colour descriptors that behave consistently with human categorization, we propose to collect psychophysical data of the membership degree of each stimulus to each colour category, and subsequently, to fit our model to this data.

Colour space

As it has been previously introduced, we will fit psychophysical data with computational colour representations that are derived from device-dependent spaces. We will use a set of images acquired by the equipment of the surveillance application in which this work is framed. Therefore, an RGB representation is directly obtained.

In order to deal with colour variability we have applied the comprehensive normalization defined by Finlayson et al.[5]. This normalization deals with changes in both the intensity and the colour of the illuminant. Dependence to intensity changes is removed by a pixel normalization which projects RGB co-ordinates on the chromaticity diagram. Independence to illuminant colour changes is achieved by a channel normalization. Due to specific conditions provided by the surveillance application, we can assume certain constancy on the image content. Such assumption can be used to improve this normalization as it has been proposed by Vanrell et al.[6]. Once the colour space has been normalized, colour information can be considered on a two-dimensional space without loose of information. Figure 1 shows an scheme of how this space, which we will denote as *uv* space, is derived.

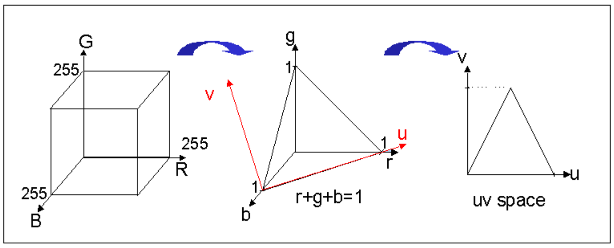


Figure 1. Colour transformations for uv space

Comprehensive normalization, removes intensity from colour information. However, for a colour naming task the intensity component might be essential. Hence, we propose to add an intensity axis, denoted by *I*, which will correspond to the original intensity in the RGB space normalized by the mean intensity of the whole image. Again, the assumption of image content constancy allows us to consider *I* as an intensity descriptor.

Psychophysical data

To build the learning set for this colour naming modelling process, we have made a psychophysical experiment[7] to obtain all the necessary data. In this experiment, 10 subjects were asked to distribute, for each stimulus, 10 points between the eleven basic colour terms proposed by Berlin and Kay[4] (black, white, red, green, yellow, blue, brown, purple, pink, orange and grey). A total of 422 colour samples were selected for the experiment which was done twice by all 10 subjects. This makes a total number of 8440 observations. For each sample, the results were averaged and normalized to the [0,1] interval. Each sample was also labelled with the colour term which had received the highest value.

The selection of only the eleven basic colour terms was made in order to reach a high degree of consistency and consensus in the colour naming task, which is highly desirable in our application. The analysis of the results of the experiment showed that subjects were consistent in their two scorings for the same sample, 85.09% of the time. The consensus between the ten subjects was achieved for 72.99% of the samples.

The colour learning set we have built with this experiment will allow us to present a preliminary approach of the colour naming system. However, it should be extended to a more complete set of samples which cover a bigger extension of the chromaticity diagram. It would be interesting to test the model on more complete sets and on standard colour spaces. Unfortunately, up to this moment, we have not found public available data of a similar experiment, since colour naming experiments does not usually ask for membership degrees to colour categories.

Modelling membership functions

As we have stated before, the goal of our work, is to define a set of characteristic functions which provide a similar response as the one that would give a user of the surveillance system. Hence, for a given colour stimulus $x=(u,v,I)$, we will obtain a colour descriptor *CD* with the membership values m_i (i=1,…,k) for each colour category C_i:

$$CD(x) = (m_1,\ldots,m_k) \qquad (1)$$

where *k* is the number of colour categories considered. In our case, we will consider k=9 categories which correspond to the eight chromatic basic colours proposed by Berlin and Kay, plus an achromatic category including white, black and grey. For this category, denoted by the term 'grey', a thresholding step on the intensity is applied to distinguish between these three colours.

Our first attempt to model the colour naming space was to select a multivariate Gaussian function as characteristic function for each colour category:

$$G(x,\mu,S)=\exp\{(-1/2)(x-\mu)^T S^{-1}(x-\mu)\} \qquad (2)$$

where μ is the mean of the samples and S is the covariance matrix. The values of μ and S were estimated for each colour category as:

$$\mu = \Sigma_j x_j/n \qquad (3)$$

$$S = (1/n)\Sigma_j(x_j-\mu)(x_j-\mu)^T \qquad (4)$$

where j=1,….,n and n is the number of learning samples for the category considered. Notice that in this first approach, the membership values obtained in the experiment, are not used. To evaluate the error committed by this Gaussian model, we computed the mean squared error (MSE) between the values given by the model and the values obtained in the experiment. The resulting MSE was 0.3485, which indicated that the colour naming modelling was far of our goal and should be improved.

Following the direction initiated by Lammens, our second approach was to use the knowledge about the membership values of learning data obtained from the psychophysical experiment and estimate the parameters of the model, such that the MSE of the fit was minimized. The estimation of the parameters was performed as a non-linear least-squares data fitting by the Gauss-Newton method. The MSE of the fit was reduced to 0.1105. Despite of this improvement, some facts indicate that the Gaussian model is only adequate to model the grey category. On the one hand, the MSE obtained for some of the categories should be improved. On the other hand, if the intensity component is eliminated, the membership maps over the uv plane derived from the experiment show that the membership values for the remainder categories (red, green, yellow, blue, brown, purple, pink and orange), are not normal distributions.

These facts took us to look for other mathematical models to represent the membership functions. The previous results allow us to define the desirable properties that should fulfil a characteristic function, $f(u,v)$, for the cited colour categories:

- $f(u,v) \in [0,1]$, in order to be a membership function.
- f has a plateau form.
- f is a parametrical function with a parameter controlling the slope of the surface.
- f is a parametrical function with a parameter allowing asymmetry with respect to the $u=v$ axis.

Several functions were considered to achieve the above constraints. However, the best results have been got when using a combination of two well-known functions. The first three constraints are fulfilled by using a Sigmoid function. To reach the last one, we propose to modulate the Sigmoid with a Gaussian function in the direction perpendicular to u=v. The Sigmoid function in one dimension is defined as:

$$S(x,\beta) = 1/(1+exp(-\beta x)) \qquad (5)$$

where β is a parameter that controls the slope of the function. Hence, we define the Sigmoid function in two dimensions for our uv space as:

$$S(u,v,\beta_u,\beta_v) = (1/(1+exp(-\beta_u u)))*(1/(1+exp(-\beta_v v))) \qquad (6)$$

The form of the Sigmoid function in the uv space, for $\beta_u=\beta_v=3$ and $\beta_u=\beta_v=20$ can seen in figure 2. Notice that $S(u,v,\beta_u,\beta_v)$ has a plateau form in the first quadrant.

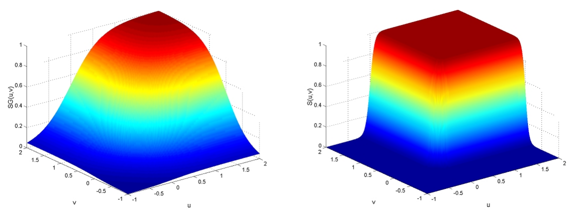


Figure 2.2D-Sigmoid function for $\beta_u=\beta_v=3$ and $\beta_u=\beta_v=20$.

Once the Sigmoid function has been defined, we define the 1D-Gaussian function which we have proposed to modulate the Sigmoid function as:

$$G(u,v,\mu,\sigma) = exp\{(-1/2)(((u-v/sqrt(2))-\mu)/\sigma)^2\} \qquad (7)$$

where μ is the mean and σ the standard deviation. Figure 3 shows an scheme of the purpose of this function.

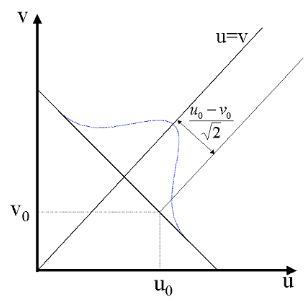
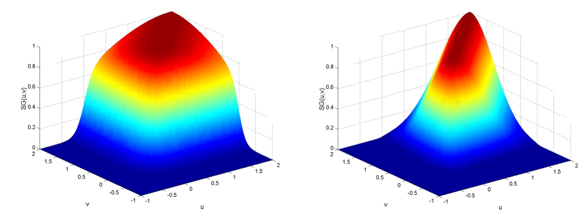


Figure 3.A 1D-Gaussian function is used to modulate the Sigmoid in the direction u=v. For a point (u_0, v_0) the Sigmoid function is modulated by the value of the Gaussian at the position $(u_0 - v_0)/sqrt(2)$.

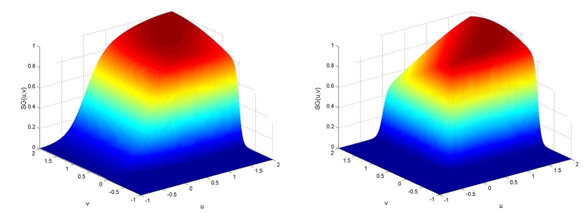
Hence, the final expression for our proposed model, which will be used as characteristic function for each color category is:

$$SG(u,v,\beta_u,\beta_v,\mu,\sigma) = S(u,\beta_u)\cdot S(v,\beta_v)\cdot G(u,v,\mu,\sigma) \qquad (8)$$

In figure 4, some examples of the Sigmoid-Gaussian function can be seen for different values of the parameters.



a) $\beta_u=10,\beta_v=10,\mu=0,\sigma=1.5$ *b) $\beta_u=20,\beta_v=20,\mu=0,\sigma=0.5$*



c) $\beta_u=5,\beta_v=20,\mu=0,\sigma=2$ *d) $\beta_u=20,\beta_v=20,\mu=0.5,\sigma=1.5$*

Figure 4. Examples of the Sigmoid-Gaussian function for different values of the parameters.

As it has been shown, the Sigmoid-Gaussian function is defined on the uv space. Previous approaches with Gaussian models have shown the usefulness of intensity component for colour naming. Therefore, in order to consider the intensity component, we have divided the uvI colour space in three levels of intensity. The values that define the three levels have been chosen in order to isolate some categories in only one or two of the intensity levels (i.e. yellow is only present for high intensity, orange does not appear for low intensity,…). The values which divide the I component into three levels are I=1.8 and I=2.2. For each one of the three levels of intensity, all the samples inside the interval are represented on a 2D uv-plane.

Once our Sigmoid-Gaussian colour naming model has been defined, the next step is to estimate the parameters for each characteristic function. For a certain colour category C_i in a given intensity level I_j, the modelling process works as follows.

Firstly, all the samples of the learning set with intensity co-ordinate included in the level I_j are selected. From this subset, we find the sample with label C_i which is the nearest to the center of the chromaticity diagram in the uv space. This sample is translated to the origin of the uv space and the same translation is applied to all the samples in the subset for I_j. The next step is to rotate the learning data in order to place the samples of the colour category which is being modelled in the first quadrant, where the Sigmoid-Gaussian has its plateau form. An initial fixed rotation for each category is applied, but the final value of the rotation α is also estimated. Thus, five parameters must be adjusted in the modelling process: α, β_u, β_v, μ and σ. When the samples of the category to be modelled have been situated in the first quadrant, the parameter estimation is again performed as a non-linear least-squares data fitting by the Gauss-Newton method.

The process described above is repeated for each colour category in each intensity level, except for the grey category. As we have mentioned before, the grey category is well modelled by a multivariate Gaussian function. Hence, after the eight chromatic categories have been modelled, the parameters of a 2D multivariate Gaussian function are estimated for each intensity level.

The results of the parameter estimation performed for the Sigmoid-Gaussian model are presented on tables 1 to 4.

Table 1. Model parameters for I < 1.8

Colour	α	β_x	β_y	μ	σ
Red	1.18	40	69	0.06	0.01
Brown	1.13	283	397	0.01	0.05
Green	-0.74	60	62	-0.02	7.54
Blue	-1.95	188	64	-0.05	0.03
Purple	2.17	322	155	-0.01	0.18

Table 2. Model parameters for 1.8 < I < 2.2

Colour	α	β_x	β_y	μ	σ
Red	1.47	64	80	0.03	0.03
Orange	0.89	50	99	0.04	0.06
Brown	0.79	255	383	-0.04	0.07
Green	-0.39	52	164	0.23	17.56
Blue	-2.19	238	145	-0.01	0.02
Purple	2.01	330	294	0.00	0.04
Pink	2.00	61	68	-0.05	0.02

Table 3. Model parameters for I > 2.2

Colour	α	β_x	β_y	μ	σ
Red	1.64	107	14	0.00	0.03
Orange	0.93	70	78	-0.02	4.04
Brown	0.35	-16	38	0.00	0.02
Yellow	0.37	477	111	0.01	0.01
Green	-0.44	75	409	-0.09	23.67
Blue	-2.41	149	174	-0.01	0.02
Purple	2.16	464	209	0.01	0.03
Pink	1.52	328	534	0.00	0.04

Table 4. Model parameters for the grey membership functions with $\mu=(\mu_1, \mu_2)$ and $S=(\sigma_0\ \sigma_1;\ \sigma_1\ \sigma_2)$

Level	μ_1	μ_2	σ_0	σ_1	σ_2
Int <1.8	0.64	0.42	0.0015	0.0001	0.0001
1.8<Int<2.2	0.65	0.43	0.0006	0.0001	0.0001
Int >2.2	0.64	0.42	0.0006	0.0001	0.0001

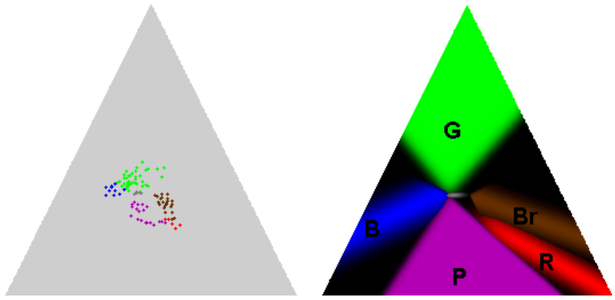


Figure 5. Samples Learning set (left) and membership values for intensity level I < 1.8

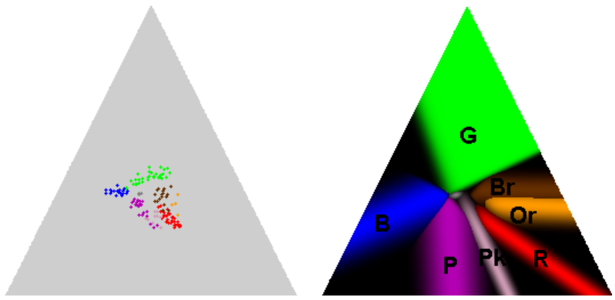


Figure 6. Samples Learning set (left) and membership values for intensity level 1.8 < I < 2.2

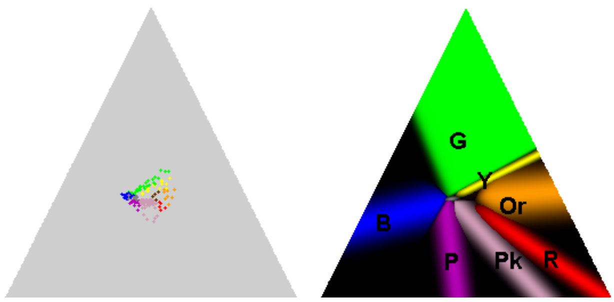


Figure 7. Samples Learning set (left) and membership values for intensity level I > 2.2

On the left part of figures 5, 6 and 7, there are the learning subsets which have been used to estimate the parameters of the characteristic functions for each level of intensity. On the right part of the same figures, we have represented the membership values for each category. As it can be seen in these figures, most of the characteristic functions occupy a narrow band in the chromaticity diagram, leaving gaps between the different colour categories. In most of these cases, the same gaps can be found in the diagram of the corresponding learning subset. This fact indicates that more colour samples should be included in the learning set, in order to cover a wider area of the chromaticity diagram with the estimated characteristic functions.

Results

In order to evaluate the results obtained by the statistical modelling of the colour naming space, we have done a comparative analysis between our Sigmoid-Gaussian model and the Gaussian-based models that have been presented before.

The psychophysical experiment described above, has provided us a set of membership values for all the samples in the learning set. Hence, the experiment results have been considered the target values for the output of the characteristic functions. During the statistical modelling of the colour naming space, the mean-squared error (MSE) between the values returned by the models and the ones obtained in the experiment has been used as a goodness measure of the model fit to the colour data.

However, as the main goal of a colour naming system is to assign a colour term to a colour stimulus, we should also evaluate the validity of the model in terms of the number of samples which are correctly named. The naming of a colour sample is performed by just assigning the label corresponding to the colour category with the highest membership value.

The models considered in the analysis are the Gaussian model estimated without taking into account the results of the experiment, the Gaussian model fitted to the experiment data and the Sigmoid-Gaussian model. All three models have been tested over the described uvI space, but also over the uv space without considering the intensity component. Notice that the Sigmoid-Gaussian model over uvI space corresponds to the three intensity levels scheme described in the previous section. The results obtained by the three models are presented in table 5.

Table 5. Results.

Model	Colour Space	MSE	% of Correct Colour Nam.
Gaussian	uv	0.2755	85.07%
Gaussian	uvI	0.3485	92.42%
Fitted Gaussian	uv	0.1634	86.02%
Fitted Gaussian	uvI	0.1105	91.94%
Sigmoid-Gaussian	uv	0.1396	85.55%
Sigmoid-Gaussian	uvI	0.0726	92.42%

Although for a given colour space, the percentage of correct colour naming is approximately the same for the three models, results in terms of the MSE show the improvement provided by the use of the membership values obtained from the experiment in the colour naming space modelling. Moreover, the fact that MSE falls to 0.0726 for our Sigmoid-Gaussian model confirm the suitability of the statistical modelling of the colour naming space by non-Gaussian models. Finally, we should notice the fall in the performance of the models in terms of the MSE and in the percentage of correct colour naming, when the intensity dimension is eliminated. This result shows the importance of intensity component for colour naming.

Conclusions

In this paper, we have proposed a non-Gaussian model for statistical modelling of a colour naming space. This model, based on a 2D-Sigmoid function modulated by a 1D-Gaussian function, is used as characteristic function for colour categories in a fuzzy-set approach to the colour naming problem.

The model is fitted to a set of psychophysical data obtained from an experiment we have done. Although this learning set includes a wide set of colour samples, it is far from being a complete learning set. This fact, has caused some problems which could be solved by building a more complete colour data set.

Nevertheless, results obtained in terms of MSE between the output of the model and the values obtained from the experiment confirm the suitability of the Sigmoid-Gaussian model as a colour membership function for colour naming.

To go further with this work, it would be interesting to validate the modelled space with other sets of psychophysical data. There are several previous colour naming experiments with large sets of data where a basic colour term is assigned to a given stimulus [8,9,10,11,12] but we are not aware of any experiment asking for membership assignments to the basic colour terms.

Moreover, the model, should also be tested on a real test set, in order to evaluate its performance in a real problem.

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Biography

Robert Benavente is a research fellow in the Computer Science Department of the Universitat Autònoma de Barcelona and is affiliated of the Computer Vision Center. He received his MSc degree in Computer Vision from the Computer Vision Center in 1999. In addition, he participates in the development of industrial applications related with quality control processes based on computer vision. His research interests include colour perception and representation, and colour naming.