ESANN'2009 proceedings, European Symposium on Artificial Neural Networks - Advances in Computational Intelligence and Learning. Bruges (Belgium), 22-24 April 2009, d-side publi., ISBN 2-930307-09-9.

SVM-based learning method for improving colour adjustment in automotive basecoat manufacturing

Francisco J. Ruiz[1], Núria Agell[2] and Cecilio Angulo[1] *

1- Universitat Politècnica de Catalunya - GREC Research Group
Av. Víctor Balaguer s/n, 08800 Vilanova i la Geltrú - Spain school

2- Universitat Ramon Llull - ESADE Business School
Av. Pedralbes 60-62, 08034 Barcelona - Spain

Abstract. A new iterative method based on Support Vector Machines to perform automated colour adjustment processing in the automotive industry is proposed in this paper. The iterative methodology relies on a SVM trained with patterns provided by expert colourists and an actions' generator module. The SVM algorithm enables selecting the most adequate action in each step of an iterated feed-forward loop until the final state satisfies colourimetric bounding conditions. Both encouraging results obtained and the significant reduction of non-conformance costs, justify further industrial efforts to develop an automated software tool in this and similar industrial processes.

1 Introduction

Automated colour matching software tools used in the colour industry are based on the theory developed by Kubelka and Munk [1] in the 1930s claiming that each colourant contributes to the absorption and scattering of the material proportionally to its amount in the system. Two different paint manufacturing tasks in the automotive industry can be distinguished: the *formulation task* and the *adjustment task*. The formulation task concerns the process of finding an appropriate set of pigments and their proportions, in order to produce a target colour. Both the set and proportions of pigments are normally found using a previously-created colour provided by a costumer. Once the formulation task is completed and accepted by the customer, the adjustment task is performed whenever a new batch is made for the production line, being the process of correcting the manufactured colour in order to achieve the original designed colour with a desired precision.

Some commercial soft-computing tools have been developed to help in the colour formulation task. For instance, FormTools [2, 3] and ColorXpress Select [4], based on the Case-Based Reasoning methodology, have been developed at General Electric Plastics. The precision level of this software depends on the size of the database. In the case of colour matching in plastics, they are currently

*The authors would like to thank the Research and Development Department of PPG Ibérica in Valladolid (Spain) for providing the research facilities used in this study. The authors also wish to gratefully acknowledge the encouraging given by Mr. Luis Ibáñez, PPG Ibérica's General Director.

managing more than 50,000 previously-matched colours on file [3]. In other manufacturing areas such as car painting in the automotive industry, no such large databases exist and would take a long time to build-up due to cost and time considerations. As a first attempt to solve the colour adjustment problem in the automotive industry, this research presents an innovative iterative procedure based on a specifically adapted type of Support Vector Machines (SVM) [5], which can be easily extended to other similar processes where an objective should be achieved through a series of actions. Two kind of experiments based on two different criteria has been specifically designed for this work and were carried out to validate our proposal. Results from experiments reveal that both considered criteria are valid to carry out an automatic tool for adjustment colour task, however some advantages were appreciated in using expert criterion as output over the criterion based on objective measurements.

The remainder of this paper is organised as follows. In sections 2 and 3, the colour adjustment problem is presented and the new methodology is formalised. Section 4 describe the experiment performed and analyse the results obtained. Finally, Section 5 presents some conclusions and future research lines.

2 The colour adjustment task

Adjustment is the process of tuning a certain colour previously obtained from a formula in order to maintain the required precision. The adjustment procedure starts by producing an initial colour with pigment percentages lower than those in the recipe. The fine adjustment is performed under the supervision of an expert who iteratively decides from experience what pigment must be added and in some extent, in what proportion, to adjust the initial colour to the target. In most cases, final proportions are substantially different from the initial proportions and unfortunately sometimes the process ends with an unrecoverable colour.

In this context, two sets will be defined. An input set is defined as the used percentages of pigments involved in the recipe. Hence, if k pigments take part in a specific colour, a $k-1$ dimensional space can be considered, the *pigmentary space*. an output set is defined from the colourimetric coordinates of the colour, the *colourimetric space*. Several numeric specifications for colour can be found in the literature. In 1976, the CIE proposed the CIE L*a*b* (CIELab) colour scale as an attempt to linearize the perceptibility of colour differences [6]. The three parameters in CIELab represent the luminance (L) of the colour, its position between red and green (a) and its position between yellow and blue (b). Once the L*a*b* position of a standard colour has been determined, a zone of tolerance can be drawn around this point for visual acceptability, indicating colours that are undistinguished by the human eye. The spectrophotometer is the most accurate and widely used in industrial colour applications type of instrument for objective colour measurement.

The perfect mapping between the colourimetric and the pigmentary spaces is too complex to be obtained from a small set of data, hence a less exhaus-

ESANN'2009 proceedings, European Symposium on Artificial Neural Networks - Advances in Computational Intelligence and Learning. Bruges (Belgium), 22-24 April 2009, d-side publi., ISBN 2-930307-09-9.

tive knowledge solution will be implemented, imitanting the colourists' iterative behaviour when tuning colours.

3 Formulation of the new method

A system is determined at a given moment by its state $S_i \in S$. In the case of adjusting colour, the state of the colour system is determined by the colourimetric coordinates measured by a spectrophotometer. For each state S_i, a number of possible actions A_i is associated. A particular case is when A_i is the same set of actions for all the states. Similar to a state machine, when an action $a \in A_i$ is carried out, a transition takes place so that the system moves from the state S_i to the state S_j. For deterministic state machines, it is verified that the final state is a function of the actual state S_i and the performed action a, $S_j = F(S_i, a)$.

For the adjusting task, an order relation $\succcurlyeq$ is defined in the set of states S, *to be more favorable than*, induced by the distance measure in the metric space,

$$S_j \succcurlyeq S_i \Longleftrightarrow d(S_j, S^*) \leq d(S_i, S^*) \tag{1}$$

where S^* is the target state. In particular, the Euclidean distance in the colourimetric space is defined as,

$$d(S_i, S_j) = \Delta E_{ij} = \sqrt{(L*_i - L*_j)^2 + (a*_i - a*_j)^2 + (b*_i - b*_j)^2} \tag{2}$$

It was originally claimed that CIELab was a perceptually uniform colour-space but, gradually it became clear that it was not. Some corrections (CIE 1994, CIE 2000 and CMC) have been added to the latest formula for consider measuring colour differences according to the eye's ability to detect differences between colours. Our proposed method will be evaluated by considering also a second order relation in S based only on the expert opinion, omitting the objective colourimetric mesasurements of the colours. Differences when considering both order relations in S will be analysed in the experiments' section.

The automated colour adjustment process begins with the construction of the training set, i.e., a set of input-output elements $\{(S, a), \theta\}$, where input (S, a) is a pair 'state-action' and $\theta \in \{-1, 1\}$ is the output (provided either, by using the colourimetric distance or by the expert), taking the value 1 for $S' = F(S, a) \succcurlyeq S$, and -1 otherwise. This training set will be fed to the classifier which will induce the order relation *to be more favorable than*.

Once the training process has been completed, the learning machine is now ready to be used jointly with an actions' generator (see Fig. 1). From an initial state S_0, the actions' generator selects a set of actions $\{a_{01}, a_{02}, ..., a_{0m}\} \subseteq A_0$ conforming the set of input patterns $\{(S_0, a_{01})$, (S_0, a_{02}),...,$(S_i, a_{0m})\}$. Patterns are classified either, class 1 or class -1 ('more favorable than' or not 'more favorable than') depending on the output sign. The algorithm associates each pattern to its distance to the discriminant surface. Hence, this value acts as fitness level of the obtained states and can be used for selecting the more appropriated action from the present state when the expert advice is used as output.

ESANN'2009 proceedings, European Symposium on Artificial Neural Networks - Advances in Computational Intelligence and Learning. Bruges (Belgium), 22-24 April 2009, d-side publi., ISBN 2-930307-09-9.

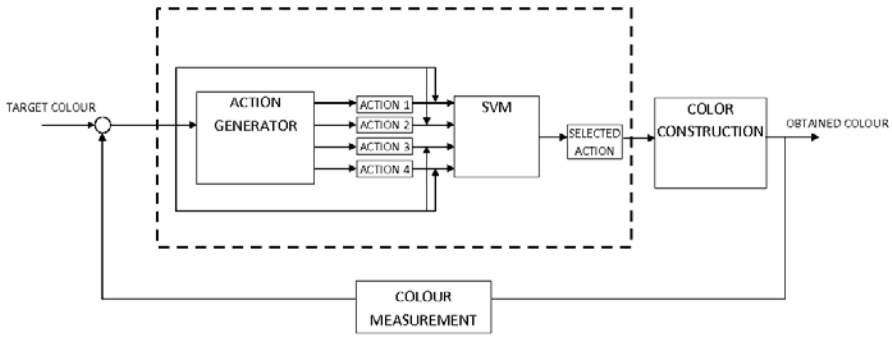

Fig. 1: Outline of the automated process: the interaction of the classifier and the actions' generator allows achieve the target colour in a loop.

Once the best action is selected, it produces a transition of state– a new colour. The new colour is also fed to the "actions' generator - learning machine" system. This process is iterated until the target colour is achieved, i.e. until $d(S_j, S^*) \leq \delta$, with S^* the objective state and δ the admitted error. The whole outline of the process is depicted in Fig. 1.

4 The colour adjustment experiments

The experiment was designed on a particular zone of the colour spectrum inhabited by red colours. According to expert colourists, colour adjustment in this zone is suitable for valid experimental analysis and discussion. The target colour, composed of four different pigments, is called *Coral Red*. Experimentation was performed under real industrial conditions for colour adjustment at the R&D Department of PPG Ibérica in Valladolid (Spain).

Tests were carried out to cover the pigmentary space for training a SVM. This kind of classifier is particularly efficient and more competitive than other methods when only a small number of sample patterns are available. This is the case in this work, where obtaining sample patterns is expensive, due to the process cost.

Following the industrial protocol and starting from a initial colour, a set of training patterns state-action is obtained combining the states $S_i = (L^*_i, a^*_i, b^*_i)$ with a set of four actions, consisting of adding one of the four composing pigments in a fixed amount $(\Delta p^i_1, \ldots, \Delta p^i_m) \in A_i$. Hence, input patterns (S, a) for training are composed of seven features. Each action determines a new state. The nearest colour to the targeted Coral Red colour according to its CIELab Euclidian distance is used to obtain four more patterns, and so on. When none of the new colours obtains a lower distance from the target than the earlier colour, the fixed amount of pigments is reduced. For experimentation purposes, a set of 188 patterns was drawn up.

ESANN'2009 proceedings, European Symposium on Artificial Neural Networks - Advances in Computational Intelligence and Learning. Bruges (Belgium), 22-24 April 2009, d-side publi., ISBN 2-930307-09-9.

	Expert opinion		
Objective class	Good	Bad	Indifferent
Good	43	8	9
Bad	29	62	37

Table 1: Expert-based and CIELab-based labeling of input patterns.

A Boolean class {good, bad} is associated with each pattern according to whether the colour obtained after adjustment is more similar to the target colour that before adjustment. Two different criteria are used and compared. The first criterion is to consider objective CIELab colour measurements and the second one is to use the expert criterion. These two criteria do not always agree. A third class was also defined in the case of expert criterion because for some patterns, experts cannot appreciate whether or not the colours are suitable for reaching the target colour. Table 1 shows the distribution of patterns in the objective and subjective classes.

The training procedure for the SVM – usual bi-class for CIELAb labeling and one-versus-one multi-class architecture for expert-based labeling – was implemented using a standard Gaussian kernel for several width values σ. It was realized during experimentation that small variations in this parameter did not have a significant influence on the results. Several values of the regularization parameter C were also tested. The accuracy of the classification obtained by the algorithm was evaluated using the leave-one-out (loo) cross-validation technique.

Table 2 shows the percentage of success varying values for the parameters σ and C using both criteria, objective CIELab measurement and expert advice. About 90% accuracy was reached using the expert criterion, even if three categories are considered for this case, whereas with the objective criterion based on CIELab measurements, success was rather more than 80%. The higher percentage of success using the expert advice suggests that the criterion used by the colour matcher is easier to learn, softer, and more acceptable than the Euclidean distance in the CIELab space. After discussion with colour matchers, it was concluded that expert opinion is preferable as output because it extracts weighting relations between L*,a*,b* measurements on the colourimetric space that Euclidian measurement cannot capture. In this sense, it is well-known that the zone of colours that is not distinguishable from a targeted colour is not a sphere. Experts are capable of implicitly inferring weighting relationships, simplifying the search space.

The above conclusion can be also supported from the geometrical point of view of the regularization parameter C. When the objective criterion was used best accuracy was obtained for $C = 1$ indicating a poor generalization whereas when using the subjective criterion best results were obtained for $C > 10000$. Finally, it is important to realize that these percentages of success correspond to a single step of the colour adjustment iterative process. Hence, a percentage of success of 90% in a one step ahead procedure will produce a slight increase in

σ/C	10^0	10^2	10^4	10^6	10^0	10^2	10^4	10^6
0.1	81.38	79.79	79.79	75.00	79.26	85.64	89.89	88.83
0.3	**85.64**	80.32	78.72	77.66	82.45	85.11	89.36	88.83
0.5	84.57	83.51	79.26	74.47	83.51	85.64	89.36	88.30
0.7	82.98	82.45	78.72	75.00	84.04	87.23	89.89	89.89
0.9	82.98	82.45	78.72	76.06	85.11	87.23	**91.49**	**91.49**
1.1	81.91	81.91	79.79	75.00	85.11	88.30	**91.49**	**91.49**
1.3	81.91	79.79	79.26	74.47	85.64	86.70	**91.49**	**91.49**
1.5	81.91	80.32	78.72	76.06	86.70	86.70	90.96	90.96
1.7	81.91	80.32	80.32	76.06	86.70	87.77	90.96	90.96
1.9	82.45	79.79	80.32	77.13	86.70	88.30	89.36	89.36

Table 2: Percentages of success using the objective (left) and the expert (right) criteria. Best accuracy results are shown in bold.

the number of steps necessary to obtain the final colour, however, the process is made up of several steps, so the percentage of success for the whole process is much higher.

5 Conclusions

Adjusting colour processes involves an expensive experimentation procedure for the industry specialising in paint production requiring continuous advice from expert colour matchers whose training presents serious difficulties. This paper describes an approach to resolve this problem by using an SVM-based iterative procedure. The results obtained encourage the design of a decision-making software tool with experts undergoing a continuous training process, and the colour adjustment task being proposed for the software. This methodology is relevant for manufacturing processes where expert supervision is required, specifically in highly creative processes for perfume, food and beverage sectors.

References

[1] P. Kubelka and F. Munk, Ein beitrag zur optik der farbanstriche, *Zeitschrift fur technische Physik* 12:593-601, 1931.

[2] W. Cheetham and J. Graf, Case-based reasoning in color matching. In D.B. Leake and E. Plaza editors, proceedings of the *2nd international conference on case-based reasoning* (ICCBR-97), Lectures Notes in Computer Science 1266, pages 1-12, Springer-Verlag, 1997.

[3] W. Cheetham, Tenth anniversary of the plastics color formulation tool, *AI Magazine* 26(3):51-61, 2005.

[4] W. Cheetham, Benefits of case-based reasoning in color matching. In D.W. Aha and I. Watson editors, proceedings of the *4th international conference on case-based reasoning* (ICCBR-01), Lectures Notes in Computer Science 2080, pp. 589-596, Springer-Verlag, 2001.

[5] N. Cristianini and J. Shawe-Taylor, *An Introduction to Support Vector Machines and Other Kernel-based Learning Methods*, Cambridge University Press, 2000.

[6] F. Billveyer, *Principles of Color Technology*, 2n edition, Jonh Wiley & Sons, 1981.