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A learning system for adjustment processes based on human sensory perceptions

Francisco Javier Ruiz[a,c], Núria Agell[b,c,*], Cecilio Angulo[a,c], Mónica Sánchez[a,c]

[a] UPC BarcelonaTech, Barcelona, Spain
[b] ESADE, Universitat Ramon Llull, Barcelona, Spain
[c] Knowledge Engineering Research Group, Barcelona, Spain

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Abstract

Creating, designing and adjusting products are essential decision processes underlying creative industries, such as painting, perfume, food and beverage industries. These processes require the participation and continuous supervision of professionals with highly-developed expert sensory abilities. Training of these experts is very complex due to the difficulty of transmitting intuitive knowledge obtained from perception. A new methodology for capturing this sensory expert knowledge that relies on a machine learning tool, previously trained with 'state-action' type patterns, jointly with an actions generator module, is proposed in this work. The method is based on a closed loop architecture together with the decomposition of complex sensory knowledge into basic elements capable of being handled by standard machine learning systems. A real case application to color-adjustment in the automotive paint manufacturing industry is presented showing the potential benefits of the method.

Keywords: Artificial cognitive systems; Expert knowledge management; Color adjustment; Color formulation

1. Introduction

Industries with specialized professionals that use their sensory abilities for designing, formulating and tuning their products, are faced with huge challenges when managing and disseminating these skills (Seaborn, Hepplewhite, & Stonham, 2005; Wright, 2010). In particular, perfume, food, beverage, painting, and other creative industries continuously deal with problems in modeling processes based on the cognitive ability of these highly specialized individuals (Allais, Perrot, Curta, & Trystram, 2007; Banerjee et al., 2012).

Creative processes are not purely functional or physical, but arise from highly subjective perceptive and cognitive aspects which cannot be completely modeled by standard quantitative structures. In these tasks, the intervention of human experts, including colorists, perfumers, chefs, sommeliers, or brew masters, becomes necessary, preventing the complete process automation. Two different design tasks involving these highly specialized human experts can mainly be distinguished: the *formulation task* and the *adjustment or tuning task*. On the one hand, the formulation task concerns the process of finding an appropriate set of ingredients and their proportions, and how to combine them in order to get a target product. Once the formu-

* Corresponding author at: ESADE, Universitat Ramon Llull, Barcelona, Spain.
E-mail addresses: francisco.javier.ruiz@upc.edu (F.J. Ruiz), nuria.agell@esade.edu (N. Agell), cecilio.angulo@upc.edu (C. Angulo), monica.sanchez@upc.edu (M. Sánchez).

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lation task is completed, the product is ready to be manufactured in the production phase.

On the other hand, the adjustment or fine-tuning task is performed during manufacturing (Bondioli, Manfredini, & Romagnoli, 2006; Herrera et al., 2010). This task must be performed whenever the product is nearly finished and has to be corrected in order to achieve the target product with the desired precision and quality. In the adjustment process, the expert, based on his/her sensory experience and abilities, determines slight variations in the proportions of one or more ingredients or variations in the combination processes. The expert intuition usually does not allow him/her to know the exact quantities to increase to achieve the goal or target. However, he/she is able to iteratively determine the approximate quantities to add or actions to perform in a closed loop control process until the final target is met. Adjustment tasks require a lot of highly qualified human and time resources. Costs associated to this kind of tasks are economically considered quality non-conformance costs, i.e. costs derived from fixing failures to accomplish specific requirements. They are usually expensive and affect the firm's profit margin and its competitiveness.

This paper introduces an innovative artificial cognitive system to support decision-making in adjustment processes based on human sensory abilities. The proposed system, based on expert knowledge management, draws on a machine learning tool jointly with an actions generator module. A Support Vector Machine (SVM) (Boser, Guyon, & Vapnik, 1992) is previously trained with 'state-action' type patterns provided by experts. Then, it enables the identification and selection of the most adequate action among those provided by the generator module for a particular state. The coupled actions generation-selection process is iterated until the final state satisfies certain conditions, i.e. until the target is achieved. The main contributions of the methodology proposed are twofold. Firstly, it proposes how to decompose complex sensory knowledge into basic elements capable of being handled by standard machine learning systems. Secondly, it follows expert behavior performing an adjustment process within a closed loop architecture.

The proposed system aims to reduce non-conformance costs when employed in a software tool. In addition, it will reinforce quality assurance efforts since the customer will permanently receive conforming products. The methodology presented has been developed and tested for color adjustment in basecoat painting. However, it can be extended to other similar tuning processes in highly creative industries, where specialized professionals with sensory abilities are implied.

The remainder of this paper is organized as follows. In Section 2, the presentation of the adjustment task in sensory products manufacturing is presented. Both, the concept is outlined and the methodology is formalized. A brief introduction of the color adjustment problem together with a real-case application for automotive basecoat manufacturing is presented in Section 3, showing that the new method is a suitable tool for this purpose. Section 4 describes the experimentation performed in a real-case application that compares expert knowledge to simple metric properties of the colorimetric space. Finally, Section 5 highlights some conclusions and future tasks related to the research line followed in this work.

2. A learning system for automated adjustment processes

Our proposal considers the process of adjustment as a Deterministic Markov Decision Process (DMDP) composed mainly by a set of states, a set of actions and an immediate reward function that quantifies the benefit of choosing one or another action. In a DMDP, a policy is a function that specifies the action chosen in each state. The core problem of DMDP is to find an optimum policy, which is the policy that maximizes some cumulative function of rewards. Reinforcement Learning is a common paradigm to deal with DMDP. It comes into play when examples of desired behavior are not available and it is based on the trade-off between *exploration*, or discovery of new actions, and *exploitation*, or preference for actions that have already been shown to be useful. Our proposal, in contrast to a Reinforcement Learning paradigm, takes advantage of expert knowledge by reducing the cost of exploration part using a standard supervised machine learning to induce the policy by querying the expert.

The proposed learning method is based on capturing and representing expert knowledge to relate product composition and its properties to generate specific sensations. Specifically, the main objective is to capture experts' skills during the adjustment process to later be able to use this knowledge in a decision support system. Information will be obtained from both, the appropriate representations (characterization of product features, such as existing nomenclature and metaphorical categories, available ingredients and control parameters) and mappings (suitable transformations to achieve the target). Next, machine learning techniques will be applied to replicate the problem-solving ability found in adjustment processes, in which individuals deploy their highly trained senses.

2.1. Problem representation

Let $(\mathcal{S}, d)$ be the metric space of the set of states $\mathcal{S}$ in an adjustment process, together with a distance d. For each state $s_i \in \mathcal{S}$, a set of possible actions $\mathcal{A}_i$ (either, finite or not) is associated. Similarly to a state machine, when an action $a \in \mathcal{A}_i$ is carried out, a transition takes place and the system moves from the state s_i to the state s_j. For deterministic state machines, it is verified that the subsequent state is a function of the current state s_i and the performed action $a \in \mathcal{A}_i, s_j = F(s_i, a)$. The distance function and the target state allows us to define a complete preorder relation in the set $\mathcal{S}$.

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Definition 1. Given the metric space $(\mathcal{S}, d)$ of the set of feasible states in an adjustment process, together with a distance d, the relation *to be more favorable than*, denoted by $\succcurlyeq$, is defined as:

$$s_j \succcurlyeq s_i \iff d(s_j, s^*) \leqslant d(s_i, s^*) \tag{1}$$

where s^* is the target state.

This relation is a complete preorder, i.e. is a reflexive and transitive relation and any pair of states s_i and s_j are related to each other. A complete preorder relation is also called a *preference relation*.

A distance function is not always easily identifiable in the space $\mathcal{S}$ and also the target state is not always perfectly known in advance. On the other hand, the preorder relation defined through a distance is not necessarily a truly preference relation as used in colloquial language (the shorter way is not always the preferred way). For this reason, a new preference relation in $\mathcal{S}$ has been also considered based only on the expert opinion, avoiding objective distances to the target of the states. This preference relation will be denoted *to be expert-preferred to*, and will be noted $\succcurlyeq_e$. In this work, we are interested in comparing a preference based on a mathematical distance with another based on the expert opinion which has not been directly obtained by its coordinates. In Fig. 1, the equipreference curves are schematically depicted considering the distance in the metric space (left) and also considering a fictitious expert opinion (right). In both cases, the target state is drawn at the center. In this figure, two additional states s_1 and s_2 are considered. We can realize that two preference relations do not always agree.

Differences due to the preference relation choice in $\mathcal{S}$ will be analyzed in the experiments' section. These differences highlight that expert knowledge based on sensory perceptions can be more complex than a simple distance in state space.

The state's preference, induced by either preference relations defined above, is considered to determine which action has to be performed in each state in the adjustment task. This is achieved by means of the so called *binary reward*.

Definition 2. Let $\mathcal{A} = \bigcup_i \mathcal{A}_i$ be the set of all feasible actions whatever the state. A *binary reward* associated with a preference relation ($\succcurlyeq$ or $\succcurlyeq_e$) is a function $\pi : \mathcal{S} \times \mathcal{A} \rightarrow \{-1, +1\}$ so that

$$\pi(s, a) = 1 \iff F(s, a) \succcurlyeq (\succcurlyeq_e) s \tag{2}$$

Binary reward using $\succcurlyeq_e$ is the smallest piece of expert knowledge related to any possible pair of state-action. It is based on the fact that experts are normally unable to predict the exact effect of an action, i.e. they ignore function F. Experts only know if an action improves or does not improve the state in the sense that the state obtained after performing the action will be more or less *expert-preferred* than the previous one. However, although binary reward contains less information than the preference relation, it is possible to roughly reconstruct the preference relation by means of the binary reward and a suitable learning system.

Fig. 2 illustrates 9 examples of state-action pairs. The binary reward when $\succcurlyeq$ or $\succcurlyeq_e$ is used is represented by a solid (1) or dashed (-1) vectors. The objective of our approach is to induce the essence of the preference relation from a set of examples.

2.2. The automated adjustment process

The automated replication of the adjustment process begins with the training set generation, i.e., a set of input–output elements $\{(s, a), \theta\}$, where input (s, a) is a 'state-action' pair and $\theta \in \{-1, +1\}$ is the output binary

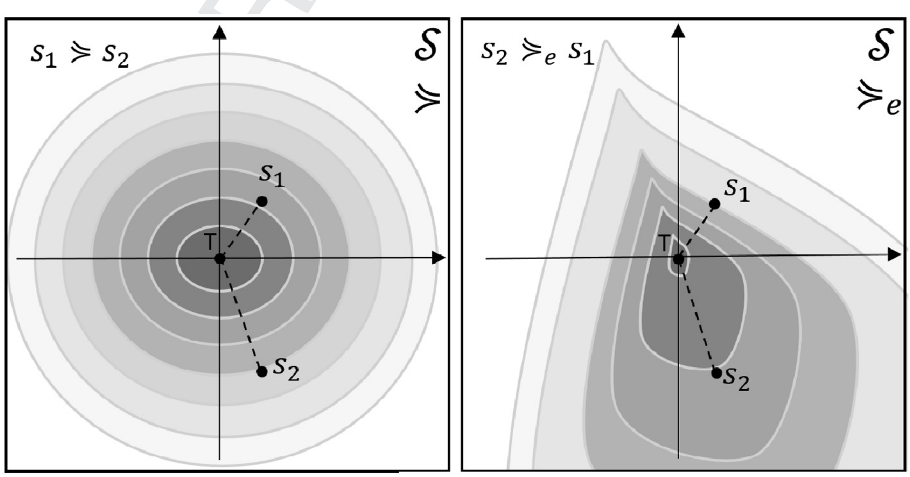

Fig. 1. Equipreference curves considering the distance in the metric space (left) and also considering a fictitious expert opinion (right). In both cases, the target state is drawn at the center. Two other states s_1 and s_2 are considered. We can realize that two perference relations do not always agree: in the first case $s_1 \succcurlyeq s_2$ and in the other case $s_2 \succcurlyeq_e s_1$.

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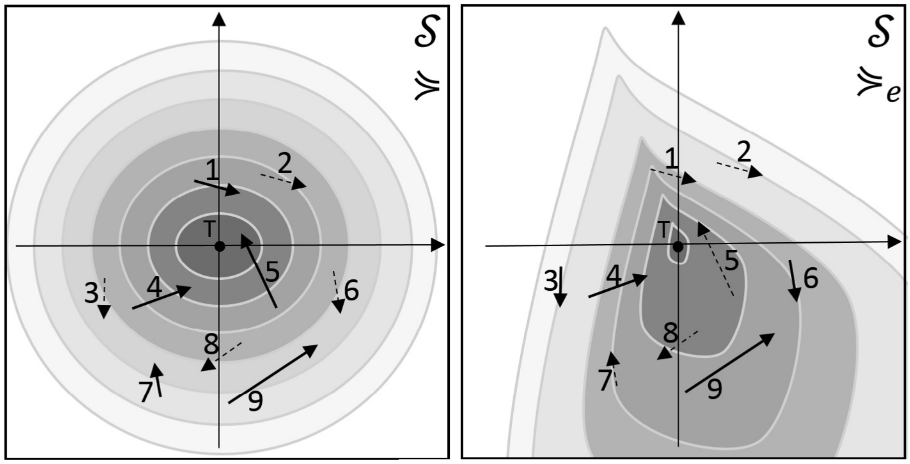

Fig. 2. 9 examples of state-action pairs and the binary reward when $\succcurlyeq$ (left) or $\succcurlyeq_e$ (right) is used. Binary reward equal to 1 is represented by a solid vector and binary reward equal to -1 is represented by a dashed vector. We can realize that the same examples can have different binary rewards depending on the preference relation considered.

reward (provided either, by using the metric distance or by the expert), taking the value $+1$ for $s' = F(s,a) \succcurlyeq s$ (or $s' = F(s,a) \succcurlyeq_e s$), and -1 otherwise. This training set is fed to a two-class learning system. In this task, we have selected a Support Vector Machine (SVM) because of its capacity for converting the binary information from the training set into a ranking output. More formally, from a two-class training set, a SVM constructs a hyperplane in a high- or infinite-dimensional feature space. This hyperplane has the largest distance to the nearest training data point of any class (in feature space) and it can be proved that in general, the larger the margin the lower the generalization error of the classifier.

SVMs are a class of learning algorithm that combine a strong theoretical motivation from the Statistical Learning Theory, optimization techniques, and the kernel mapping idea (Boser et al., 1992). The original input vector from the input space X is mapped by means of a proper kernel function to a higher-dimensional feature space $\mathcal{F}$ where the pattern discrimination is simpler, i.e. where a linear separating hyperplane exists.

Each hyperplane in a feature space is determined by the expression $\mathbf{w} \cdot \mathbf{x} + b = 0$ where $\mathbf{x} \in \mathcal{F}$. It does not matter if $\mathcal{F}$ is an infinite dimensional space since, in practice, the discriminant function is written in terms of the original patterns from input space X, the kernel function and Lagrange multipliers obtained by solving the dual optimization problem. The SVM algorithm searches for the separating hyperplane maximizing the margin, in other words, maximizing the minimum distance between the hyperplane and the training patterns. Training patterns closest to the hyperplane are known as support vector and the hyperplane depends only on them.

Each training data point has a position in the feature space (that normally is unknown because the feature space is only implicitly determined by the kernel). The hyperplane not only allows knowing in which of the two hyperspaces the pattern belongs. Before taking the sign, the output of the SVM algorithm is related to the distance of the new pattern to the hyperplane in the feature space. This way, the hyperplane can induce an order relation in feature space and hence in the input space whatever its dimension.

Once the training process has been completed, the learned machine is now ready to be used jointly with an actions generator (see Fig. 3). The actions generator is the module containing the restrictions and prior knowledge of the problem to be solved. This generator proposes to add only those ingredients available and compatible with the product. The efficiency of the method depends heavily on this module.

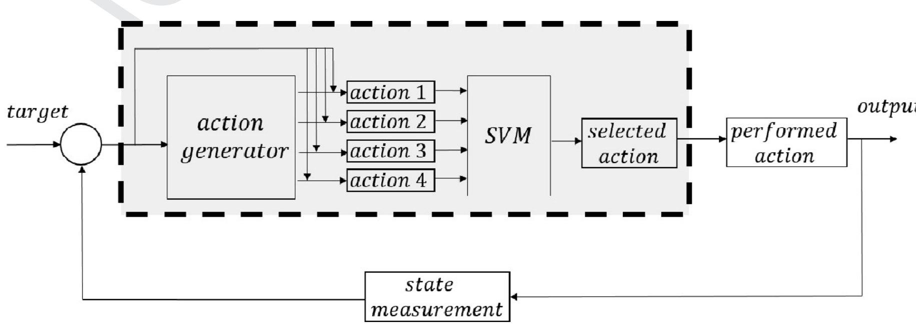

Fig. 3. Outline of the automated process: the interaction of the classifier and the actions generator allows achieve the target state in a close loop structure.

From an initial state s_0, the actions generator selects a set of actions $\{a_{01}, \dots, a_{0m}\} \subseteq \mathcal{A}_0$ to the set of input patterns $\{(s_0, a_{01}), (s_0, a_{02}), \dots, (s_i, a_{0m})\}$. The SVM classifies these patterns either, as class $+1$ or class -1 ('more or less favorable than'). The algorithm ranks the actions and selects the most appropriate action from the current state.

Once the best action is selected, this action produces a transition of state, a new product. The new state is also fed to the "actions generator - learning machine" system. This process is iterated until the target product s^* is achieved, i.e. until $d(s_j, s^*) \leqslant \delta$, with s^* the objective state and δ the admitted error. The whole outline of the process is depicted in Fig. 3.

3. Illustrative framework in automotive basecoat manufacturing

In the automotive industry, paints and coatings are currently applied both, to protect vehicles from environmental corrosion and to improve their consumer appeal. Paint is fundamentally made up of binder, solvents and pigments. Binder is a non-volatile resin or polymer that actually forms a film for the finished paint product. Solvents are the part of the paint or coating product that evaporates. Their role is to keep the paint in liquid form for ease of application. Once applied to the surface they evaporate, leaving an uniform film which then dries to form a protective coating. Pigment is composed of insoluble particles and it forms a suspension in the binder. Pigments are the main components that influence the final color. They serve for several purposes: to hide the surface on which they are applied, to provide a decorative effect through the particular color of the paint film, and to provide surface durability. Pigments and binder are permanent components of paint, but only pigments significantly influence the definitive color of the surface. The exact proportions of pigments in a paint constitute the color recipe. Hence, if k pigments take part in a specific color, a $k-1$-dimensional space can be considered, the *pigmentary space*. Each element or point in this space represents a different color recipe.

Automated color matching software tools used in the color industry are based on the theory developed by Kubelka and Munk (1931) in the 1930s. Their approach considers pigment particle scattering and absorption interaction on a global, instead of a particle, level. Using this approach, Kubelka and Munk proposed the still state-of-the-art equations used in the pigment industry. According to their theory, each colorant contributes to the absorption and scattering of the material, and its contribution is proportional to its amount in the system multiplied by an absorption and scattering coefficient. These equations are based on non-exact assumptions, hence obtained results do not completely agree with the real results at the precision level that is nowadays required by the automotive basecoat industry. In addition, this theory uses pigment absorption and scattering coefficients that are difficult to obtain and they may significantly vary from one pigment batch to another.

Some commercial soft-computing tools have been developed to help in the color formulation task. For instance, FormTools (Cheetham, 2005; Cheetham & Graf, 1997) and ColorXpress Select (Cheetham, 2001), based on the Case-Based Reasoning (CBR) methodology, have been developed at General Electric Plastics. Both tools, also based on the equations of Kubelka-Munk, provide effective management of color formulation and adjustment databases, as well as easily allow the integration of these databases with measurement instruments, usually spectrophotometers. The precision level of this software depends on the size of the database. In the case of General Electric Plastics, they are currently managing more than 50,000 previously-matched colors on file (Cheetham, 2005) for color matching in plastics. However, in other manufacturing areas such as car painting in the automotive industry, no such large databases exist, and it will take a long time to build them up due to cost and time considerations. Therefore, the precision required nowadays by the automotive industry for the color formulation task cannot be fully achieved using existing tools.

3.1. The color formulation and adjustment tasks

Automobile manufacturers handle a range of colors for their products that are periodically modified due to several reasons, like new components or new fashion trends. Paints are ordered from specialized companies who, from a simple sample chip, have to find out a recipe for the color. These companies have a certain number of recipes in their databases for the colors they are normally provide. Formulation is the process of finding out an appropriate set of pigment and their proportions in order to produce a targeted color. They are normally obtained from a near, but different, previously-created color. On the other hand, adjustment task is the process of tuning a certain color, previously obtained from the formula, in order to maintain the required precision. Even for previously-manufactured color formulae, differences between pigments acquired in different batches and inaccuracies in the production process produce unavoidable irregularities in the final product. So, it is usually not possible to directly obtain the targeted color from the formula with the desired precision without the adjustment phase.

A formulation task is implemented once in a 'color life', whereas adjustment tasks must be completed whenever a new batch is used. The final adjustment task is at least as expensive as color formulation, requiring a lot of human and time resources, because a color matcher's training is complicated due to the difficulty of transmitting intuitive knowledge. Although many efforts have been made to automate the formulation process, the adjustment process has always been considered as inevitably manual.

The adjustment procedure starts by producing an initial color from colors that are already known with pigment per-

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centages lower than those in the recipe, i.e. with the paint vehicle (binder and solvent) in a higher proportion. From this initial color, a fine adjustment is performed under the supervision of an expert. He or she is able to decide from experience and intuition what pigment must be added and, to some extent, in what proportion, in order to adjust the initial color to the target. This process takes place in an iterative experimentation that unfortunately sometimes ends with an unrecoverable color. In most cases, final proportions are appreciably different from initial proportions.

3.2. The pigmentary and the colorimetric spaces

In the color adjustment context, two sets of variables must be considered: variables involved in the recipe, that is, pigments and, more precisely, their used percentages, that in this case are better known as *pigmentary space*, and variables defining the color obtained in the colorimetric coordinates, better known as *colorimetric space*. A perfect knowledge of the mapping from the colorimetric to the pigmentary space would completely solve the problem of color adjustment, with differences between batch pigments being dealt with as noise. However, this mapping is too complex to be obtained from a small set of data, so a less exhaustive knowledge solution is proposed, imitating the colorists' or colors matchers' behavior when tuning colors.

Several numeric specifications for color can be found in the literature. The most classic and internationally accepted of these is that based on tristimulus values, first RGB and later XYZ, proposed by the *Commission International de l'Eclairage*(CIE) in 1931. In 1976, the CIE proposed the CIE $L^*a^*b^*$ color scale, based directly on the CIE 1931 XYZ color space, as an attempt to linearize the perceptibility of color differences (Billveyer, 1981).

CIE $L^*a^*b^*$ (CIELab) is the most complete color model used conventionally to describe colors visible to the human eye. Its three parameters represent the luminance (L) of the color, its position between red and green (a) and its position between yellow and blue (b). Some years later, the CIE adopted revisions to $L^*a^*b^*$ calculations which led to $L^*C^*h^*$ color tolerance (also known as CIELCh). This color model uses the basic CIELab information, but presents the graphical information with a focus on chroma (C) and hue (h) that may be visually easier to understand than typical CIELab graphical presentations. CIELCh converts the CIELab linear coordinates into (C,h) polar coordinates, L remaining as the lightness/darkness coordinate. The geometrical representation of the two color models is depicted in Fig. 4. Once the $L^*a^*b^*$ or $L^*C^*h^*$ position of a standard color has been determined, a zone of tolerance can be drawn around this point for visual acceptability, indicating colors that are undistinguished by the human eye.

The spectrophotometer is the most accurate and widely used in industrial color application types of instruments for objective color measurement, offering robust measures for

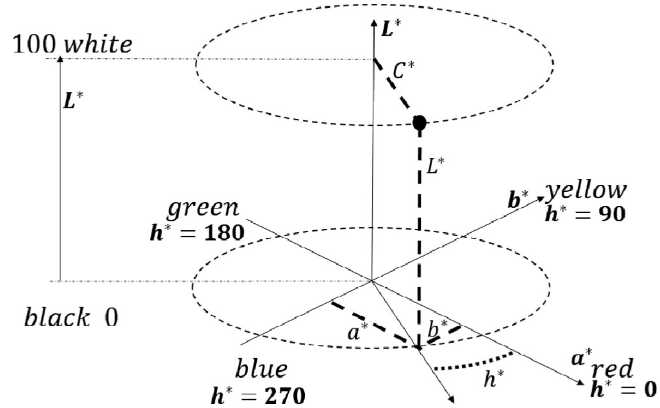

Fig. 4. The CIE $L^*a^*b^*$ and $L^*C^*h^*$ geometrical coordinates systems.

all the angles and standard lighting conditions. It measures individual wavelengths and then calculates $L^*a^*b^*$ or $L^*C^*h^*$ values from this information, providing an objective way to consistently quantify color differences and thus facilitate the management of product color tolerance. Colors can be characterized through these sets of numbers, $L^*a^*b^*$ or $L^*C^*h^*$, conforming the coordinates of a colorimetric space.

No colorimetric space is yet accepted by color matchers as a unique objective color measure. Therefore, visual inspection is still necessary to establish appreciable differences between colors. Besides, new color spaces are being defined in the literature attempting to capture human vision features (Seaborn et al., 2005).

4. An experimental application to color adjustment

An experimental application to show the validity of the presented methodology was performed under real industrial conditions for color adjustment over a period of six months at the central laboratory at the Research and Development Department of PPG Ibérica S.A., located in Valladolid (Spain).

The experiment is focused on analyzing the difference between the preference relation based on colorimetric space distance and those based on expert opinion.

In the process of color adjustment, many factors can produce colorimetric changes: procedure of application, thickness of the painting layer, ambient humidity, temperature, drying time, and so on. The more complex the pigmentary formula, the more easily these factors will influence the color observed. In order to diminish this effect, a color without sophisticated visual effects (aluminum and micas) was selected as a real-case for experimentation. The experiment was designed on a particular zone of the color spectrum inhabited by red colors. According to expert colorists, color adjustment in this zone is suitable for valid experimental analysis and discussion. The target color is called *Coral Red*, which is composed of four different pigments in its initial formula.

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4.1. Experimental design and data set

Following the industrial protocol and beginning with 10 initial colors or initial states near the target color, a set of state-action training patterns was obtained combining states with a set of four actions. Each action consists of adding one of the four composing pigments in a fixed amount, i.e. from each initial color, four separate adjustments are made. Each action determines a new state (a new color). At this point, 10 groups of 4 state-action patterns have been generated. In each group, the closest obtained color to the target according to its CIELab Euclidian distance was used to obtain four more patterns using the same actions, and this process was carried out five times. When none of the new colors achieved a lower distance from the target than the earlier color, the fixed amount of pigments was reduced. Each series of four tests carried out is accompanied by a test of confirmation of the best result of the previous series, for ensuring equality of conditions of temperature and humidity. Thus, a set of training patterns is completed. After obtaining $10 \times 4 \times 5 = 200$ state-action patterns, 12 of them were discarded due to manufacturing discordances, therefore a set of 188 patterns was built for the experimentation.

During the experimental process of color adjustment, the state of a color is defined by its CIELab colorimetric coordinates, $s_i = (L^*_i, a^*_i, b^*_i)$, $i = 1, \ldots, 188$, and the set of actions associated to the state consist of adding a certain quantity of pigments $(\Delta p^i_1, \Delta p^i_2, \Delta p^i_3, \Delta p^i_4) \in \mathcal{A}_i$, $i = 1, \ldots, 188$. Consequently, in our experiments, each of the training input patterns (s, a) is composed of seven features $(L^*_i, a^*_i, b^*_i, \Delta p^i_1, \Delta p^i_2, \Delta p^i_3, \Delta p^i_4)$, being the first three components the colorimetric coordinates of the initial color (the state) and the remaining four components a vector in the pigmentary space that represents the adjustment being made on a certain pigment (the action). Note that action consists of a 4-dimensional vector with only one component different from 0.

Two methods were used to label the training patterns. The first method was only based on the colorimetric coordinates measured by the spectrophotometer. A pattern was labeled as +1 if the Euclidean distance in colorimetric space between the obtained color and the target was less than the distance of the original color to the target. In this case, the expert opinion was not taken into account. On the other hand, the labelling task was obtained querying an expert. The expert assigned each pattern to a class of three (*suitable*, *unsuitable* or *indifferent*). The third class has been defined because for some of patterns, experts cannot appreciate whether or not the colors are suitable for reaching the target color. All the computations were performed using the R computing language (Development Core Team et al., 2005) and the *e1071* package available from the CRAN R repository (*cran.r-project.org*).

4.2. Analysis and discussion of the results

Pattern distribution using the assignation criteria is shown in Table 1. For the most, but not all, of the patterns both criteria agree. Disagreements show that expert knowledge are not only based on distance criteria.

The training procedure for the SVM was implemented using a standard Gaussian kernel, considering several values for width σ. It was realized during the experimentation that a small variation in this parameter did not have a significant influence on results. Several values of the regularization parameter C were also tested. When expert labels were employed, *suitable* as taken as class +1 and *unsuitable* and *indifferent* as taken as class −1, this way the two assignation criteria could be compared using a two-class SVM.

In order to evaluate the accuracy of the classification obtained by the algorithm, the leave-one-out (loo) cross-validation technique was employed. Results in percentage of success are depicted in Tables 2 and 3, varying values for the parameters σ and C using both criteria, objective CIELab measurement and expert advice.

Results from experiments reveal that both criteria are valid to carry out an automatic tool for the adjustment color task, however some advantages were appreciated in using expert criterion as output over the criterion based on the objective measure. Using the expert criterion, about 90% accuracy was reached, whereas with the objective cri-

Table 2
Accuracy using the CIELAB metric (objective criterion).

σ/C	10^0	10^2	10^4	10^6
0.1	81.38%	79.79%	79.79%	75.00%
0.3	**85.64%**	80.32%	78.72%	77.66%
0.5	84.57%	83.51%	79.26%	74.47%
0.7	82.98%	82.45%	78.72%	75.00%
0.9	82.98%	82.45%	78.72%	76.06%
1.1	81.91%	81.91%	79.79%	75.00%
1.3	81.91%	79.79%	79.26%	74.47%
1.5	81.91%	80.32%	78.72%	76.06%
1.7	81.91%	80.32%	80.32%	76.06%
1.9	82.45%	79.79%	80.32%	77.13%

Table 1
Distribution of patterns in classes according to either, expert-based labelling or CIELab-based labelling.

		Expert-based			
		Suitable	Unsuitable	Indifferent	**Total**
CIELab-based	Good	*43* (23%)	*8* (4%)	*9* (5%)	60 (23%)
	Bad	*29* (15%)	*62* (33%)	*37* (20%)	128 (68%)
	Total	72 (38%)	70 (37%)	46 (46%)	**188** (100%)

Table 3
Accuracy using the expert criterion.

σ/C	10^0	10^2	10^4	10^6
0.1	79.26%	85.64%	89.89%	88.83%
0.3	82.45%	85.11%	89.36%	88.83%
0.5	83.51%	85.64%	89.36%	88.30%
0.7	84.04%	87.23%	89.89%	89.89%
0.9	85.11%	87.23%	**91.49%**	**91.49%**
1.1	85.11%	88.30%	**91.49%**	**91.49%**
1.3	85.64%	86.70%	**91.49%**	**91.49%**
1.5	86.70%	86.70%	90.96%	90.96%
1.7	86.70%	87.77%	90.96%	90.96%
1.9	86.70%	88.30%	89.36%	89.36%

terion, based on CIELab measurements, success was little more than 80%. The higher percentage of success using the subjective criterion with such a short training set suggests that the criterion used by color matchers is easier to learn and more acceptable than the Euclidean distance in the CIELab space.

After discussions with expert color matchers, it was concluded that expert opinion is preferable as output because it extracts weighting relations between L*, a*, b* measurements on the colorimetric space that Euclidian measurement cannot capture. In this sense, it is well-known that the zone of colors that is not distinguishable from a targeted color is not a sphere, so weighted Euclidean distance would be more suitable for comparisons in colorimetric space than the standard distance. Experts are able to implicitly infer these weights, hence simplifying the space.

Another analysis supporting the above conclusion was discussed from the geometrical point of view on the regularization parameter C. When the objective criterion was used as output, the best accuracy results were obtained for $C = 1$, indicating a poor generalization, and so over fitting, whereas when using the subjective criterion, the best results were obtained for a large regularization value, $C > 10,000$.

Finally, it is important to realize that these percentages of success correspond to a single step of the color adjustment iterative process. It signifies that a percentage of success of 90% in a one step ahead procedure will produce a slight increase in the number of steps necessary to obtain the final color. However, the process is made up of several steps, so the percentage of success for the whole process can be higher.

5. Conclusions and future research

In this paper a new methodology is proposed to replicate specialized professionals skills in tasks based on their sensory abilities in highly creative industries. In the proposed methodology a new learning system is suggested to capture highly subjective perceptions and cognitive aspects which cannot be modelled by quantitative systems.

The proposed approach has been developed for adjustment processes based on human-sensory perceptions and has been applied to automated color-adjustment in the automotive paint manufacturing industry. The results obtained with this methodology will contribute to a significant reduction of non-conformance costs, i.e. costs derived from a failure to accomplish a requirement of a customer, justifying further industrial efforts to develop an automated software tool in this and similar industrial processes.

The work described in this paper assumes an approach to the resolution of the color adjustment problem. As future research, we plan the design of a decision-making software tool, with experts undergoing a previous training process, and the color adjustment task being performed by the software. This software tool will automatically propose vectors in pigmentary space that will adjust the initial color to the target color.

6. Uncited references

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.cogsys.2018.06.011.

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