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Eric Benoit, Gilles Mauris, Laurent Foulloy

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E. Benoit, G. Mauris, L. Foulloy

LAMII/CESALP
Laboratoire d'Automatique et de MicroInformatique Industrielle
Université de Savoie, BP 806, 74016 Annecy Cedex, France

Abstract

The aim of this paper is to propose a new method for building a fuzzy partition on multi-dimensional spaces. This method is based on a linear interpolation performed by means of Delaunay's triangulation of the multi-dimensional space. It is applied for creating fuzzy symbolic sensors which use multi-component measurements. Colour sensing is an interesting problem for applying this method. Indeed, humans have good control on this sensing but can not explain it simply. Fuzzy colour sensors can learn human perception of colours whithout explicit knowledge about the perception mechanisms.

Keywords: fuzzy sensor, fuzzy subsets, colour sensor, multisensor

Introduction

Introduced since several years ago, *fuzzy symbolic sensors*, also called *fuzzy sensors*, are intelligent sensors which are able to receive, to produce and to handle fuzzy linguistic information [1], [2], [3]. A fuzzy linguistic information is represented by a fuzzy subset of symbols. This particularity allows them to be used as perceptive elements for symbolic controllers like fuzzy controllers and fuzzy expert systems. Furthermore, this kind of sensor can own the most advanced functionalities of intelligent sensors, like auto-adaptation and learning, by using artificial intelligence techniques as proposed by Zingales [4].

Most of the fuzzy sensors work on single-component measurements like distance, temperature and so on. They generate fuzzy linguistic information by a process called *fuzzy linguistic description*, or simply *fuzzy description*. In order to create fuzzy sensors working on multi-component measurements like colour or smell, two ways can be considered. The first strategy consists in defining the fuzzy description by means of a rule based formalism that involves a fuzzy description of every feature returned by the corresponding fuzzy sensor. It has been applied to a linguistic description of comfort [5]. The second strategy is based on an interpolation method in order to build fuzzy subsets on multi-dimensional spaces.

After having defined fuzzy sensors, the fuzzy description method based on multi-dimensional fuzzy sets is presented. In the second section, we recall the principle of colour measurement, and we apply the method to the fuzzy description of RGB components of colour and to fuzzy description of chrominance. Then a sensor which performs the fuzzy description of a coloured surface is described.

1. FUZZY SENSORS

1.1 Definition

Fuzzy symbolic sensors are based on the translation of information from a numerical representation to a linguistic one. One issue to provide a numeric-linguistic conversion is to associate a fuzzy set with each symbol in order to obtain a fuzzy measurement of physical quantities. The interest of the fuzzy subset approach is to take into account the continuous nature of the variables, inside the linguistic representation that is itself discrete.

The fuzzy meaning is a mapping from a linguistic set S into the set of the fuzzy subsets of measurements [6]. The fuzzy meaning of a symbol $\boldsymbol{a}$ is characterized by its membership function denoted $\mu_{\tau(\boldsymbol{a})}(x)$. In a same manner, a fuzzy description can be defined as a mapping from the measurement set into the set of the fuzzy subsets of symbols, so the fuzzy description is characterized by its membership function denoted $\mu_{\iota(x)}(\boldsymbol{a})$. The relation between the membership functions of a fuzzy description and the corresponding fuzzy meaning, given by Eq. (1), states that if a symbol belongs to the description of a measurement, then the measurement belongs to the meaning of the symbol.

$$\mu_{\iota(x)}(\boldsymbol{a}) = \mu_{\tau(\boldsymbol{a})}(x) \tag{1}$$

If the set of the fuzzy meanings forms a fuzzy partition of E then we have a fuzzy nominal scale [7], which is an extension to fuzzy subsets of the concept of nominal scale [8]. The meanings associated with a fuzzy nominal scale verify Eq. (2). According to Eq. (1), the fuzzy description of any measurement verifies Eq. (2).

$$\forall (x \in E),\ \sum_{a \in S} \mu_{\tau(a)}(x) = 1 \tag{2}$$

$$\sum_{a \in S} \mu_{\iota(x)}(\boldsymbol{a}) = 1 \tag{3}$$

A simple example for a fuzzy telemeter is provided in Fig. 1. The fuzzy description of the distance x = 12 cm is obtained from the fuzzy meaning of the symbols in S = {***Close***, ***Medium***, ***Far***}.

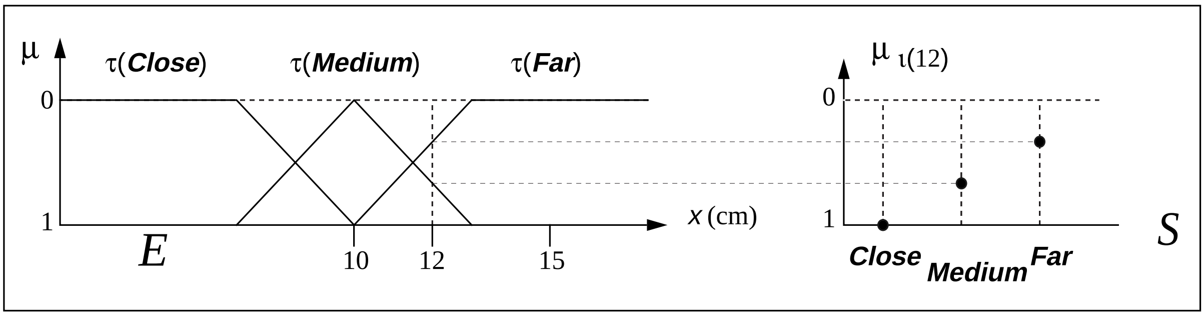

Fig. 1 Fuzzy description of the measurement x = 12 cm.

1.2 Multi-component fuzzy sensors

When a sensor uses several transducers, the measurement is a vector of numerical values. Then, the meaning of each symbol must be a fuzzy set defined in a multi-dimensional volume. Furthermore the set of meanings has to be a fuzzy partition of the measurements set.

In this paper, we consider an initial knowledge about measurements. This knowledge is materialized by the meaning of symbols on a small subset V of the measurements set E. Then we have to extend the meaning of each symbol on all the measurements set. In order to obtain a fuzzy partition, the measurements set is cut into n-simplexes. A n-simplex in a n-dimensional space is a polyhedra with n+1 vertices. For example, a 2-simplex is a triangle and a 3-simplex is a tetrahedron. Then meanings are defined on each n-simplex such that Eq. (2) is verified.

First, the measurements set is partitioned into n-simplexes using Delaunay's triangulation. The points used to perform the triangulation are the elements of the set V. As any triangulation can be used to cut the measurements set, it must be chosen according to constraints associated to the measurements [9]. The Delaunay triangulation is preferred when no constraint can be found.

The membership function of the meaning of each symbol is defined on each n-simplex by a multi-linear interpolation. We suppose the restriction on a n-simplex of the membership function of the meaning of a symbol ***s*** is:

$$\mu_{\tau(s)}(v) = \mu_{\tau(s)}(x_1, x_2, ..., x_n) = a_1x_1+a_2x_2+ ... +a_nx_n+a_{n+1} \tag{4}$$

The value of this function is known for the n+1 vertices of the n-simplex, therefore the n+1 factors a_i can be calculated.

$$A = M^{-1}B \qquad M = \begin{bmatrix} x_{1_1} & ... & x_{1_n} & 1 \\ ... & ... & ... & \dots \\ x_{n+1_1} & ... & x_{n+1_n} & 1 \end{bmatrix} \qquad A = \begin{bmatrix} a_1 \\ \dots \\ a_{n+1} \end{bmatrix} \qquad B = \begin{bmatrix} \mu_{\tau(s)}(v_1) \\ \mu_{\tau(s)}(v_2) \\ ... \\ \mu_{\tau(s)}(v_{n+1}) \end{bmatrix} \tag{5}$$

The i[th] vertex of the n-simplex is denoted v_i, and its j[th] component is denoted x_{i_j}.

Once this process is performed on each n-simplex for each symbol, we obtain a fuzzy nominal scale defined on E. This scale is an extension on E of the fuzzy nominal scale on V.

With this method, the knowledge needed for the configuration of the sensor is very compact. It can be acquired by means of a system called a teacher which can be a human or an expert system. During the configuration phase, the teacher and the sensor analyse the same phenomenon, and the teacher gives its description to the sensor. The sensor increases its knowledge with its measurement associated with the teacher description. Then it can build the fuzzy nominal scale. It should be noted that the description given by the teacher must be a fuzzy subset of symbols which verify Eq. (2). If the teacher is a human then its description is generally a crisp set which contains only one symbol.

2. FUZZY COLOUR SENSOR

2.1 Colour measurement

Human beings perceive electromagnetic light beams by four types of photochemical transducers: three cones for the day vision and one rod for the night vision. The photometric sensors give back information in relation to the received energy. The sensation of colour is generated by the different spectral sensitivities of the cones. The “blue” cones detects short wavelength, whereas the “green” and “red” cones detect respectively medium and long wavelengths.

The artificial sensing (for example the video camera) is based on three photometric transducers that recreate the effects of red, green and blue cones. Their respective sensitivity are denoted $R(\lambda)$, $G(\lambda)$, $B(\lambda)$ where λ is the wavelength. The responses of the detectors are given in Eq. (6) where $s(\lambda)$ denotes the spectrum of the light to be analysed. When the responses are normalized between 0 and 1, the colour space is simply a unit cube called the RGB cube.

$$\begin{aligned} r &= \int_{\lambda_1}^{\lambda_2} s(\lambda)R(\lambda)d\lambda \\ v &= \int_{\lambda_1}^{\lambda_2} s(\lambda)V(\lambda)d\lambda \qquad \left(with \quad \begin{aligned} \lambda_1 &= 400nm \\ \lambda_2 &= 700nm \end{aligned} \right) \\ b &= \int_{\lambda_1}^{\lambda_2} s(\lambda)B(\lambda)d\lambda \end{aligned} \tag{6}$$

When decribing a colour in the common language, the luminosity is usually separated. For example we say “pale blue” or “dark red”. In order to introduce this knowledge into the sensor, a non linear mapping is applied to the RGB cube. This mapping has been chosen in order to obtain a colour information which do not depend on the luminosity. This information (C'_1, C'_2) is called the chrominance.

$$\begin{bmatrix} C'_1 \\ C'_2 \end{bmatrix} = \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & -\frac{\sqrt{3}}{2} & \frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} \frac{r}{Y'} \\ \frac{v}{Y'} \\ \frac{b}{Y'} \end{bmatrix} \qquad Y' = max(r, v, b) \tag{7}$$

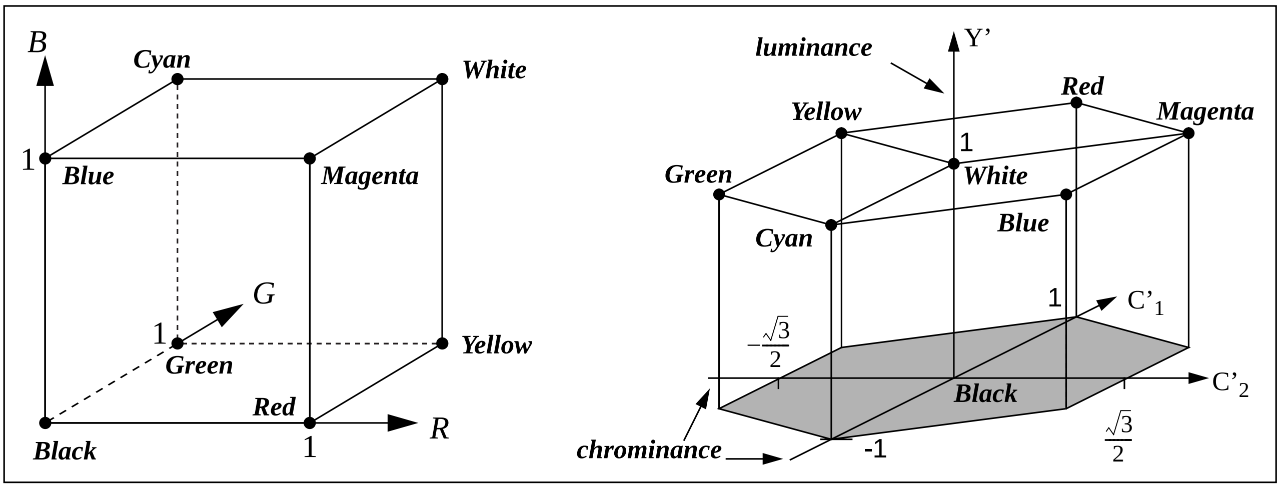

Fig. 2 The RGB cube and its transformation.

2.2 Fuzzy description of chrominance

A first way to build a fuzzy description of colours is to describe separately the luminance and the chrominance. The measurements set of the luminance is monodimensional, and its description is not developed in this paper. The measurements set of the chrominance is two-dimensional. It is called the chrominance plane of colours and it is used as the measurements set. Initially, seven colour are used for the configuration of the sensor:

S={***Neutral***, ***Red***, ***Magenta***, ***Blue***, ***Cyan***, ***Green***, ***Yellow***} (8)

$\iota(0,0)$ = {***Neutral***}, $\iota(-1/2, \sqrt{3}/2)$ = {***Blue***}, $\iota(1/2, \sqrt{3}/2)$ = {***Magenta***}, $\iota(-1/2, -\sqrt{3}/2)$ = {***Green***}, $\iota(1/2, -\sqrt{3}/2)$ = {***Yellow***}, $\iota(1,0)$ = {***Red***}, $\iota(-1, 0)$ = {***Cyan***}. (9)

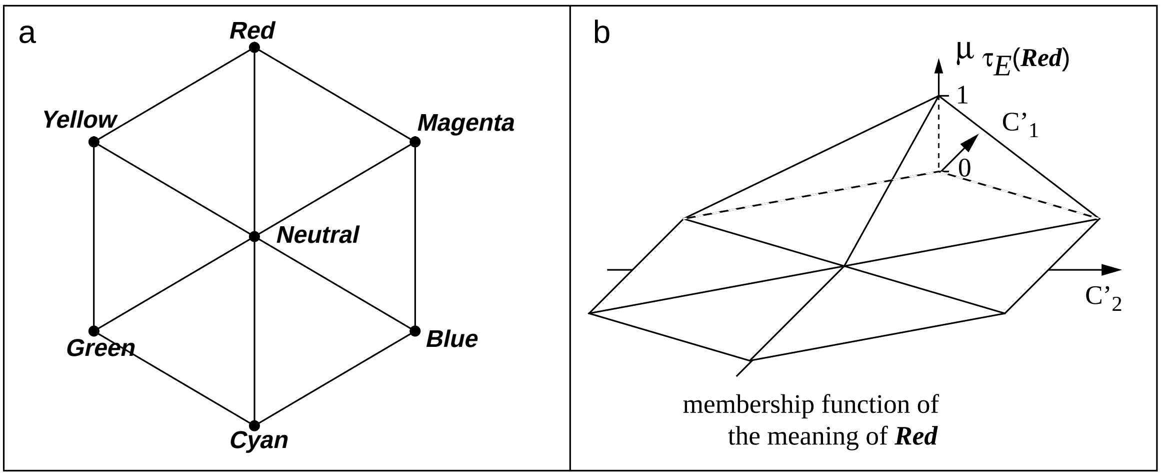

Fig. 3 Delaunay's triangulation of the chrominance plane and the fuzzy meaning of ***Red***.

Experiments show that only one or two characteristic colours are needed to perform the configuration of the sensor. The small number of configuration points can be explained by the choice of the mapping used to obtain the chrominance plane. Indeed, if two colours differ only by their darkness then they have the same coordinates in the chrominance plane. The following figure shows the result of the configuration performed to adapt the sensor to return a description of colours close to the human perception in a classification task of coloured objects. We have here four types of coloured objetc: red, yellow, green and blue objects. Each class is represented by a characteristic colour which is used for the configuration. In general, any number of class and any number of colour per class can be used to perform the configuration. The only condition is to define one symbol per class.

Fig. 4 shows Delaunay's triangulation when learning four new characteristical points, one red, one yellow, one green and one blue. A new interpolation is built which leads to a new nominal scale. The symbols have a new fuzzy meaning, see for example the fuzzy meaning of ***Red*** given in Fig. 4.

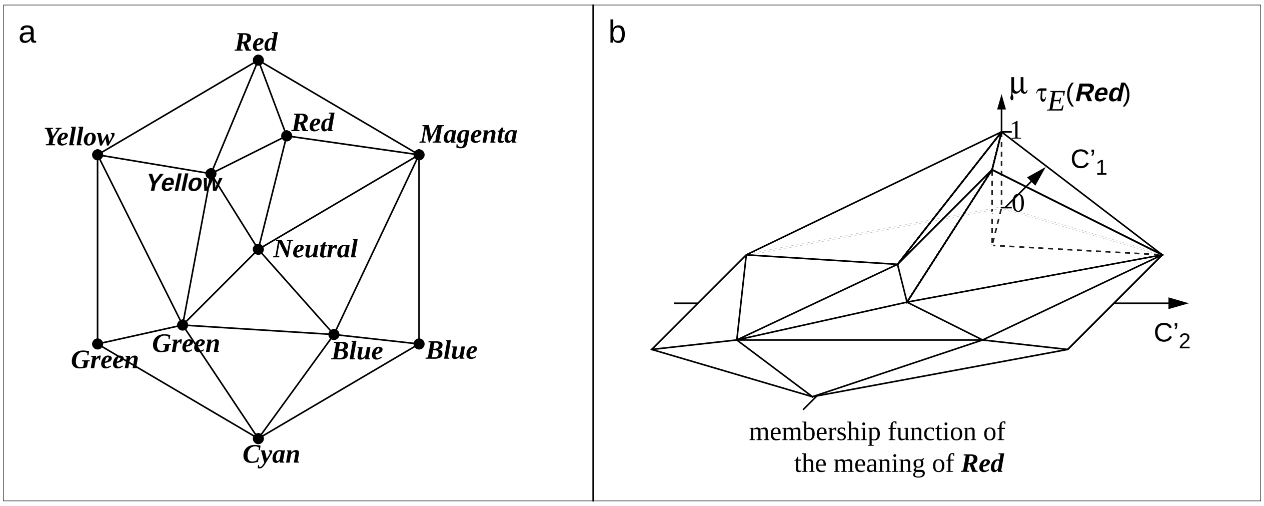

Fig. 4 New Delaunay's triangulation and new fuzzy meaning of ***Red***.

2.3 Fuzzy description of RGB components

Now, the RGB colour space is used as the measurements set of the fuzzy sensor. The characteristic points used for the triangulation are the vertices of the cube. Since the description of each vertex of the RGB cube is known, the initial linguistic set can be defined by Eq. (10).

$$\iota(0,0,0) = \{\textbf{\textit{Black}}\},\ \iota(1,0,0) = \{\textbf{\textit{Red}}\},\ \iota(0,1,0) = \{\textbf{\textit{Green}}\},\ \iota(0,0,1)= \{\textbf{\textit{Blue}}\},\ \iota(1,1,0) = \{\textbf{\textit{Yellow}}\},$$
$$\iota(1,0,1) = \{\textbf{\textit{Magenta}}\},\ \iota(0,1,1) = \{\textbf{\textit{Cyan}}\},\ \iota(1,1,1) = \{\textbf{\textit{White}}\} \qquad (10)$$

$$S = \{\textbf{\textit{White}}, \textbf{\textit{Black}}, \textbf{\textit{Red}}, \textbf{\textit{Magenta}}, \textbf{\textit{Blue}}, \textbf{\textit{Cyan}}, \textbf{\textit{Green}}, \textbf{\textit{Yellow}}\} \qquad (11)$$

Now, the triangulation can be performed, and fuzzy meanings of symbols can be calculated. If we try to use this initial configuration to describe a real colour, the result is generaly far from the desired one. For example the description of a red colour is $\iota(0.639, 0.224, 0.326)=\{0.09/\textbf{\textit{Red}}, 0.36/\textbf{\textit{Black}}, 0.22/\textbf{\textit{Yellow}}, 0.33/\textbf{\textit{Magenta}}\}$. It means that the structure of the real subset of ***Red*** colours is more complex than a single tetrahedron. Furthermore, this initial configuration based on a theoretical knowledge about colour measurements is not close to the reality. In order to define a configuration closer to the real perception, we provide to the sensor new measurements and their description. Then the sensor uses this new knowledge to perform a new triangulation, and build the new fuzzy meanings of symbols. After this learning phase, the new fuzzy description of the previous red colour is ι(0.639, 0.224, 0.326)={0.89/***Red***, 0.03/***Blue***, 0.04/***Yellow***, 0.04/***Magenta***} which is closer to the reality because the grade of membership of ***Red*** is now 0.89.

Experiments show that for several basis colours, the learning need three or four characteristic points for one symbol. Contrary to humans, the sensor makes an important difference between pale and dark colours. For example, a correct learning of ***Red***, includes pale red, red and dark red.

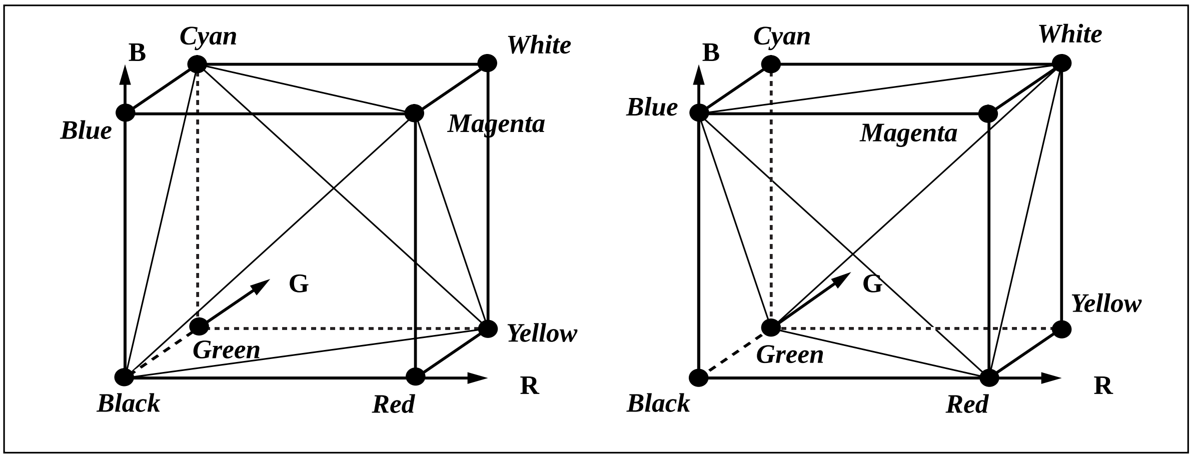

Fig. 5 This figure shows the two possible triangulations of the RGB cube. The choice of the initial triangulation is not critical: it will be totally modified during the configuration phase.

3. Application

The previous methods were applied to implement a fuzzy sensor which performs the fuzzy description of the coloured surfaces. The measurement is based on the analysis of the light reflected by an illuminated surface. The reflection phenomenon can be modelized by the combination of two cases: the diffuse reflection which is predominant for mat surfaces, and the specular reflection which is predominant for polished surfaces. In general, the light coming from the specular reflection depends only on the colour of the emitted light while the colour of the surface can be acquired by analysing the diffuse light.

The sensor has three components: a light source, a sensing unit, and a measurement head (Fig. 6). The measurement head is designed to illuminate the surface and to integrate the light coming from the diffuse reflection. The spatial integration reduces the effect of surface texture. The light source is a thermic one. It was chosen to have an illumination close to the sun light.

The sensing unit includes three transducers, a signal conditioner, and a computation device which performs the signal processing, the fuzzy descriptions and the learning. The transducers are phototransistors with optical filters. The computational device is based on a 80C196KB micro-controller, with 32Kbytes of RAM and an I2C interface for network communication. The computational device performs the configuration process and generates the fuzzy description of the analysed surface. The I2C network interface is used for the communication with the fuzzy control system, fuzzy actuators, or other fuzzy sensors.

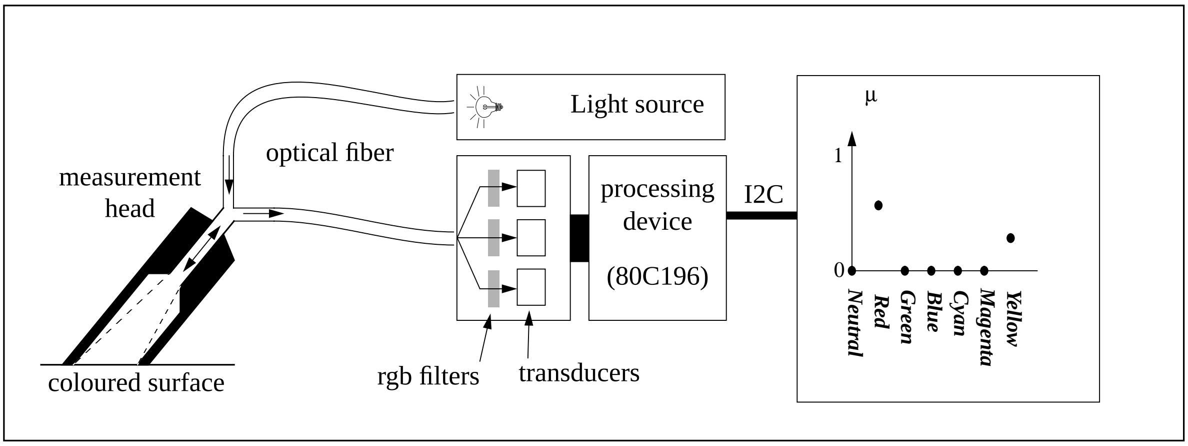

Fig. 6 Description of the fuzzy colour sensor.

Conclusion

Multi-component fuzzy sensors can be used in many domains where the measurement depends on several sources. Due to their configuration capabilities, they are especially adapted for complex sensing especially those perfomed by humans. Indeed, the sensor does not need explicit numerical model of these mechanisms to be configurated. Only a small set of measurements associated with their fuzzy or crisp description is needed.

Fuzzy colour sensors return a fuzzy representation of the measure,therefore they can be used in a rule based fuzzy control system. This ability is interesting when colours represent significant information to control the process. A simple example is the control of the colour of painting oils.

The second type of applications is classification. In this case, the measurements used for the sensor configuration are characteristic elements of classes to identify. After the configuration, the sensor is able to return at which grade a measurement is member of a class.

The method applied to build multi-dimensional fuzzy sets can be used in many applications. For example, pattern recognition is an interesting domain to apply this method.

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