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FOOD QUALITY EVALUATION ACCORDING TO THEIR COLOR CHARACTERISTICS

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Abstract. *This paper looks at some of the most important aspects related to sensory characteristics and examples of applications of color characteristics to define the quality of food products. The purpose of the study is exploring the possibilities of combining data from different sensors in order to increase the accuracy of classification of food products. For the assessment of quality there is used probabilistic neural networks. The procedure has been successfully tested to increase the accuracy in data experiments for quality classification citrus juices. The results show the potential of the proposed type of classifiers to be used as a rapid, objective and non-destructive tool for quality assessment on real recognition systems in the near future.*

Key words: *food quality, sensory characteristics, color characteristic, probabilistic neural networks*

1. INTRODUCTION

Quality control is an important aspect of food production and processing from the point of view of providing foods of acceptable nutritional value, and for providing safety of products. Several characteristics such as size, shape, density, maturity, moisture content, oil content, flavor, firmness, tenderness, color, defects, blemishes, etc., are routinely used in the quality control of agricultural and biological food products. Most analytical techniques used in quality control required isolation of the food component. The original properties of the product are, therefore, destroyed during sample preparation and analysis. Oftentimes, such analyses are expensive, time consuming, and require sophisticated instrumentation, and hence are not suited for "on-line" quality control of food products. Recent progress in the development of instrumentation utilizing of food products has provided several non-destructive techniques for quality evaluation. Some of the nondestructive methods, which

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employ optical, vibration, electrical, nuclear magnetic resonant and gas analysis techniques, have potential for commercial application [1,3].

The paper gives an overview of the main sensory characteristics defining the quality of food, as basic attention is paid to the determination of color characteristics. First attempts were made to unify the color and spectral features for classification purposes.

2. SENSORY CHARACTERISTICS

Determining how food products affect consumer's senses is one of the most important goals of the food industry. It also is a primary concern for nutritionists and dietitians. Because our five senses act as the gatekeeper of our bodies, the benefits of healthy food will be reaped only if our senses accept it. Therefore, consumer reaction, as perceived by the five senses, is considered a vital measure of food development.

People accept food on the basis of certain characteristics that they define and perceive with their senses. These attributes are described in terms of sensations and are sometimes referred to as qualitative or sensory qualities. They include perceptions of appearance factors such as color, size, shape, and physical aspects; kinesthetic factors such as texture, viscosity, consistency, finger feel, and mouth feel; and flavor factors or sensations combining odor and taste. Table 1 shows the some essential indicators of food products [1].

Table 1 Components of qualities

External Qualities		Size (weight, volume, dimension)
		Shape (diameter/depth ratio)
		Color (uniformity, intensity)
		Defect (bruise, stab, spot)
Internal Qualities	Flavor	Sweetness, Sourness, Astringency, Aroma
	Texture	Firmness, Crispness, Juiciness
	Nutrition	Carbohydrates, Proteins, Vitamins, Functional property
	Defect	Internal cavity, Water core, Frost damage, Rotten

Since its emergence in the 1940s, however, sensory evaluation has developed as an exciting, dynamic, constantly evolving discipline that is now recognized as a scientific field in its own right. The sensory professional is routinely confronted with problems which call upon an extensive skill set drawn from a range of disciplines, e.g. biological sciences, psychology, experimental design and statistics and will often be required to work with other specialists from these areas. Additional challenges are presented by working with a human 'measuring instrument' that is highly variable [7, 14].

Sensory evaluation can be divided into two categories of testing: objective and subjective. In objective testing, sensory attributes of a product are evaluated by a selected or trained panel. In subjective testing, the reactions of consumers to the sensory properties of products are measured. The power of sensory evaluation is realized when these two elements are combined to reveal insights into the way in which sensory properties drive consumer acceptance and emotional benefits. Linking sensory properties to physical, chemical, formulation and/or process variables then enables the product to be designed to deliver optimum or appropriate consumer benefits [15].

Sensory evaluation is a science that measures, analyses and interprets responses of people to products as perceived by the senses. For decades, sensory scientists have researched and developed methods to capture reactions of people to various kinds of stimuli and better understand the perceptual process, while others have used sensory information to identify successful consumer products [14].

The measurement of sensory properties and determination of the importance of these properties to consumer product acceptance represent major accomplishments in sensory evaluation. These achievements have been possible as a direct result of advances in sensory evaluation, in the application of contemporary knowledge about the measurement of human behavior, and in a more systematic and professional approach to testing.

Methods based on electromagnetic radiation correspond to the highest level of modern requirements for objective determination of quality. Fig. 1 presents some indication of the entire electromagnetic spectrum and region thereof visible to humans (VIS) range of 380 nm to 780 nm (26315.7 cm^{-1} and 12820.5 cm^{-1}) in which one sees the colors of the rainbow violet to red. The rest of the spectrum is invisible.

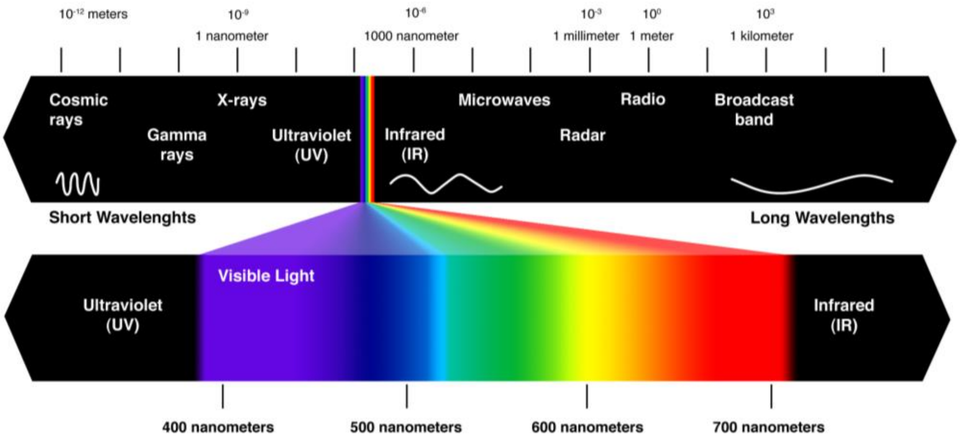

Fig. 1 The electromagnetic spectrum

3. Color Characterictics

The importance of color of agricultural commodities and processed foods cannot be overstressed. An important problem is discoloration or the fading of colors of various raw and processed fruits and vegetables. In some cases, color changes are accompanied by undesirable changes in texture, taste, or odor. Overage cheese, beer, meat, and fish all develop off-color, which the consumer recognizes as being associated with poor flavor quality. The maturity of many fruits and vegetables is closely associated with color development or changes in color. In other cases, a color change may not be actually detrimental, but nevertheless reduces consumer acceptance. Consumers expect certain foods to have certain colors, and deviation from those colors may cause sales resistance. Many of these prejudices are altogether irrational.

Obviously, far too little is known about the significance of color perception in food acceptance. Observers do associate certain colors with acceptance, indifference, or rejection. Colored lights are used to mask color differences and reduce some influence of color on sensory evaluation, but the psychological effect of colored lights has not been adequately measured. These effects may be direct, on the appeal of the food as a whole, or indirect, in influencing odor, taste, or texture thresholds. Various interrelationships suggest themselves.

The human eye has a remarkably fine qualitative discrimination for color, but is not a quantitative instrument. Consequently, precise color measurement requires modern instruments. This need is particularly felt where food products are blended to a certain standard from raw materials that differ somewhat in their color properties. The effect of climate and time of harvesting have a marked influence on the color of the raw material from which many processed foods are made.

In food related research projects, color measurement is of special significance because often we need to quantify color changes, which will bear significant correlations with process parameters or sensory parameters.

As the color varies with the amount or intensity of mixture of primary colors which form innumerable color shades, color measurement is somewhat complex. With the increasing need of reliable color measurement or color quantification methods, it has remained the focus of several research works throughout the world [2, 11, 16].

Color models. We will look at three of the most commonly used color models.

Lab model. The CIE (International Commission on Illumination) is the international authority on light, illumination, color, and color spaces. It recommended color measurement in terms of values. The CIE system of color measurement forms the basis of any color measurement system. The first color space that is mathematically defined was by the CIE in 1931. The color space is perceptually uniform and the most complete model defined by the CIE in 1976 to serve as a device-independent, absolute model to be used as a reference. It is based on *XYZ* color space as an attempt to linearize the perceptibility of color differences, using the color difference matrix described by the Macadam ellipse. The non-linear relations are intended to mimic the logarithmic response of the human eye. Here, is the luminance or lightness component, which ranges from 0 to 100, and parameters (from green to red) and (from blue to yellow) are the two chromatic components, which range from –120 to 120. Before the advancements in the computer field, this was a difficult task, but with leaps and bounds of computer advancements, suddenly there seems to be abundant ways of determining surface color properties. The values are often used in food research studies [2, 10, 13].

RGB model. RGB model is an additive color model that uses transmitted light to display colors in which red, green, and blue light are added together in various ways to reproduce a broad array of colors. The name of the model comes from the initials of the three additive primary colors, red (R), green (G) and blue (B). Various proportions and intensities of these three primary colors are used to create cyan, magenta, yellow, black and white. The model relates closely to the way human eye perceives color on the retina. The model is device dependent, since its range of colors varies with the display device.

When one of the components has the strongest intensity, the color is a hue near this primary color (reddish, greenish, or bluish), and when two components have the same strongest intensity, then the color is a hue of a secondary color (a shade of cyan, magenta or yellow). A secondary color is formed by the sum of two primary colors of equal intensity: cyan is green+blue, magenta is red+blue, and yellow is red+green. The color is expressed as an RGB triplet, each component of which can vary from zero to a defined maximum value [7, 15].

CMYK model. CMYK model is a subtractive model based on complementary colors (Cyan, Magenta, Yellow, and Black) with respect to additive color in RGB color model. In additive color models such as RGB, white is the "additive" combination of all primary colored lights, while black is the absence of light. In the CMYK model, it is just the opposite: white is the natural color of the paper or other background, while black results from a full combination of colored inks. Since RGB and CMYK spaces are both device-dependent spaces, there is no simple or general conversion formula that converts between them.

It is important to reiterate that the RGB and CMYK models are device dependent. The $L^*a^*b^*$ model has the largest gamut encompassing all colors in the RGB and CMYK gamut. While those color models are useful, their limitations should also be observed. For example, the spectrum of colors seen by the human eye is wider than the gamut (the range of colors that a color system can display or print) available in any color model [2, 10, 13].

4. MATERIALS AND METHODS

The purpose of the experiment is to unite the spectrophotometric data with color features to increase the accuracy of quality classification natural citrus juices.

Spectral properties of each product generate individual (specific and often unique) profile. This profile can potentially be used as a fingerprint to identify a particular type of quality (presence of GMOs, forgery, maturity, freshness, etc.). In this study methodology as shown in Fig. 2 was used.

The specific problem relates the determination of three classes of juice: *fruit juice* (consisting of 100% product); *fruit nectar* (no less than 25-50%) and *fruit drinks* (even lower content of fruit juice). Determined for the main quality parameters of citrus juices are collected spectral reflectance characteristics in the range of 144 samples 400-1000nm natural citrus juices of different brands available on the Bulgarian market. Reflectance spectra of the three types of product are collected using a standard cell in the black background.

The instrumental analysis for all samples include evaluation of five colors to coordinate system $CIEL^*$, a^* and b^*. Determining the color characteristics (L^*, a^*, b^*, Cab^*, hab) is measured in mode total transmission. In this case, there was used USB4000 fiber optic spectrometer (Ocean Optics, USA).

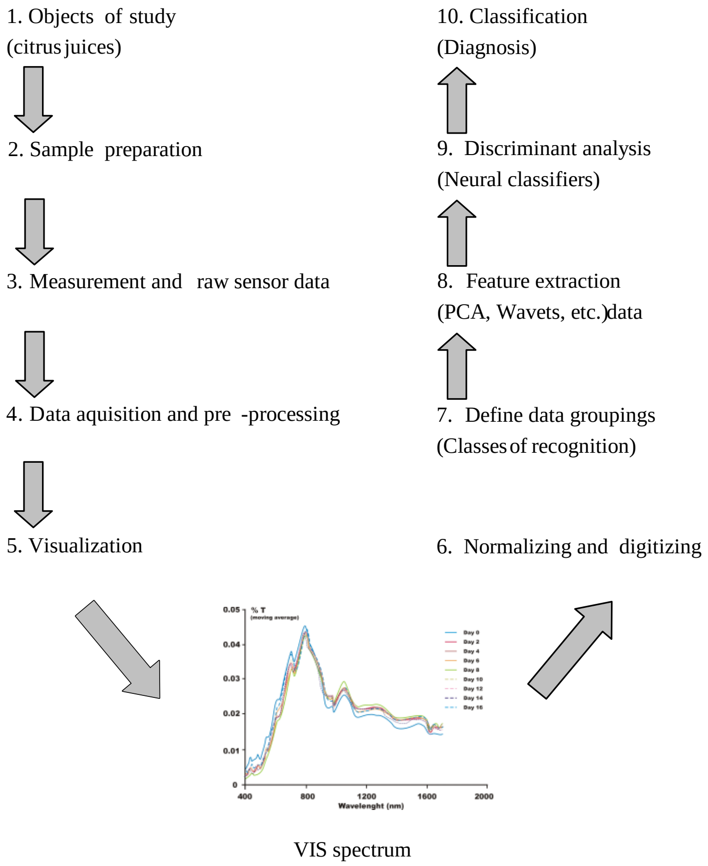

Fig. 2 A plot the general scheme illustrating the formation of the applied methodology

Probabilistic neural networks can be used for classification problems. Probabilistic neural classifiers (PNC) are a kind of radial basis network suitable for classification. These classifiers are characterized by their relatedness to Bayes strategy known from the probabilistic and statistical theory and aimed at reducing the expected risk involved in decision making and minimizing classification errors. The architecture for this system is shown below (Figure 3). A PNC is an implementation of a statistical algorithm in kernel discriminate analysis in which the operations are organized into a multilayered feedforward network with four layers: Input layer, Probabilistic layer, Summation layer and Output layer [4, 6].

In the first two layers, distances are computed from the input vector to the training input vectors and a vector is produced whose elements are converted by radial basis functions in the probability density.

According to the Bayes decision rule, if the probability density function (pdf) of each of the populations is known, then an unknown sample *U*, belongs to class *i*, if:

$$f_i(U) > f_j(U) \text{ ,all } j \neq i \text{ ,(} f_k \text{ is the } pdf \text{ for class } k \text{).} \qquad (1)$$

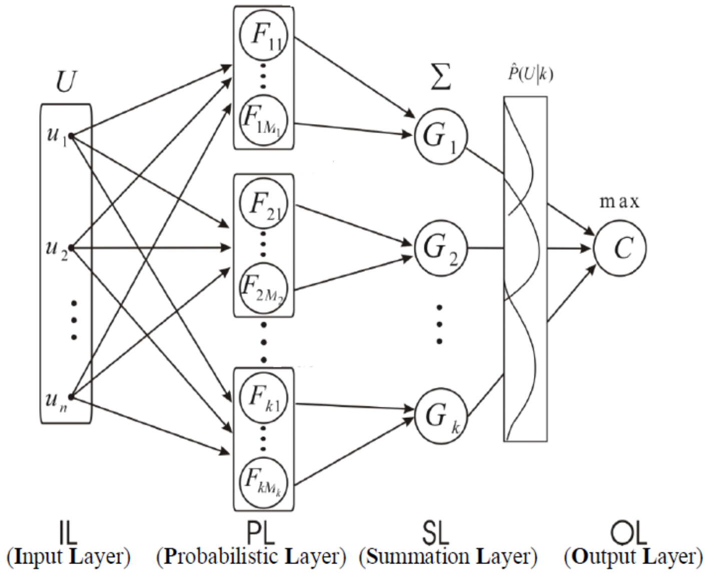

Fig. 3 Probabilistic neural network

The calculation of the *pdf* by using samples of populations (the training set - Figure 4).

In accordance with Figure 3, the input vector $U = (u_1, u_2, ..., u_n)^T \in R^n$ is applied to all *n*-neurons of input layer. Neurons of the PL-layer are divided into K groups, one for each class. The output of *i*-th neuron of *k*-th class is calculated by using a kernel function (in the case of Gaussian) having the form:

$$\hat{P}(i/k) = F_{ki}(U) = \frac{1}{(2\pi\sigma^2)^{n/2}} \exp\left(-\frac{\|U - U_{ki}\|^2}{2\sigma_{ki}^2} \right), \qquad (2)$$

where: $U_{ki} \in R^n$ is the "center" of the kernel, and σ_{ki} – spread parameter. Usually it is accepted $\sigma_{ki} = \sigma$ and this eliminates common factors and absorbs the "2" in σ in the denominators of (1):

$$F_{ki}(U) \approx \frac{1}{p_i} \sum_i^{p_i} \exp\left(-\frac{\|U - U_{ki}\|^2}{\sigma^2} \right), \qquad (3)$$

where p_i are samples in the *i*-th population.

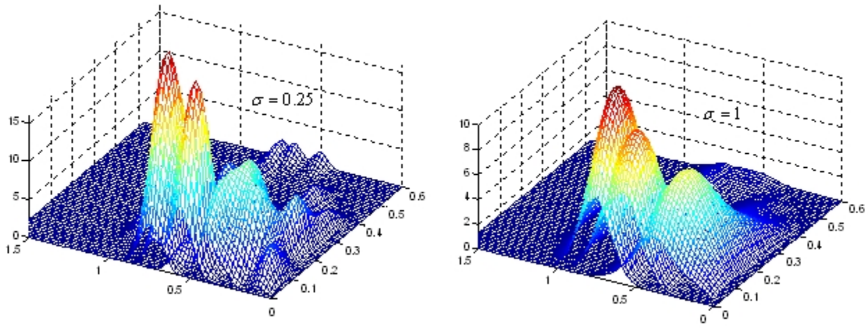

Fig. 4 Two-dimensional density probability distribution

SL-layer the network is used to approximate the conditional probabilities, by combining the thus calculated densities:

$$G_k(U) = \sum_{i=1}^{M_k} w_{ki} F_{ki}(U)\,,\ (k = 1, 2, ..., n)\,, \tag{4}$$

where: M_k – number of objects (neurons), w_{ki} – positive coefficients (weights). In accordance with the rule (1), the input vector is classified into the class, which is connected to SL-neuron with a maximum output:

$$C(k) = \arg\max_{1 \le k \le K}(G_k). \tag{5}$$

The output vector has k components. One of these components is 1 and the rest are 0. Thus, each input vector is associated with one of k classes.

Improving the accuracy of the classification in the PNC is associated with the search for the optimal value of σ and the formation of a suitable reducing training set [6]. The latter determines the number of neurons in the RBF-Probabilistic layer. PNC are realized by 144 neurons in PL-layers ($n=5$, $k=3$ and $k=2$).

The PNC is not related to some assumption about normal distribution. The features for color characteristics (L^*, a^*, b^*, Cab^*, hab) can be used without transformation, i.e. directly, as is done in exhaustive feature selection.

When comparing the spectrophotometric data derived from a complex mixture as juices, statistical data handling methods are thus an invaluable tool. Data compression methods such as principal component analysis (PCA) provide a useful way of reducing the data size without considerably reducing the amount of information that can be derived from it. In order to reduce the feature space for spectral reflectance characteristics, we used Principal component analysis (PCA) [9].

The training set must be thoroughly representative of the actual population for effective classification. The composition of the testing sample and that of the training sample were selected at random, 60% of the sample as proportional to each class is used for classifier training and 40% - for testing. Table 2 presents test set errors.

Table 2 Test set errors

Qualification test errors			Total error
Class1/ Class2	Class1:0.124	Class2:0.094	0.117
Class2/ Class3	Class2:0.057	Class3:0.083	0.072
Class1/ Class3	Class1:0.036	Class3:0.058	0.043

5. RESULT AND DISCUSSION

For the training process of a PNC, determination the value of the smoothing parameter σ is essential, that is to determine the parameter sigma using heuristic techniques. Best results were obtained by classification into two classes, and optimizing the value of parameter sigma of the Gaussian function.

Research is conducted in the MATLAB programming environment. In the individual program modules the corresponding layers of the PNC used functions toolbox Neural Networks: newpnn, dist, radbas, netprod, compet netsum, etc [8].

PNC structures applicable to the quality evaluation of natural citrus juices and orange juice in particular, were investigated. A comparison was made from the viewpoint of accuracy, speed and computer implementation.

Important advantage of probabilistic neural networks is that training is easy and that they can be used in real-time. Well-trained network can be generalized and for new samples outside the training sample.

The paper discussed the possibilities of data fusion from different sensory tools to obtain a more complete and accurate assessment of the quality of food products. The present proposal is to combine spectral and color characteristics to separate the three groups of natural citrus juice. The results show the advantages of the unite of information, which could serve as an initial step in future research on more complex assessments of performance quality and the creation of expert systems.

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