解 説

Color Recognition Systems

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色認識システムについて，主にスペクトル領域における光学的パターン認識に基づいて論ずる．初めに，空間およびスペクトル領域で作用する光学的コリレータについて簡単に述べる．続いて，スペクトル領域におけるインコヒーレントな光学的パターン認識について，最後に統計的パターン認識法およびその光学的実現法について詳しく紹介する．さらに，光学的に測定されたわずかなパラメータから色のスペクトルを正確に復元することができる線形モデルについて論ずる．

1. Introduction

Importance of color is increasing in image analysis and classification. Actually this is natural, because almost all visible objects are color objects. Thus combining spatial and spectral information more human perception kind of pattern recognition systems may be designed.

We know that there are three types of cones in the human retina. These cone groups have peak absorptions in the red, green and blue regions of visible spectrum, the absorption spectra of these receptors overlap considerably, and all spectra are essentially between 400 and 700 nm. However, it is important to note that the whole human visual process, even in the retina level is not well understood.

Much earlier than the evidence of the existence of three cone sensors was confirmed, the classical trichromatic model of human color vision was proposed. Nowadays the basic trichromatic way to determine numerical values for colors is using the CIE (Comission Internationale l'Eclairage) tristimulus values defined as

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = k\int \tau(\lambda)S(\lambda)\begin{pmatrix} \bar{x}(\lambda) \\ \bar{y}(\lambda) \\ \bar{z}(\lambda) \end{pmatrix} \mathrm{d}\lambda$$

where $S(\lambda)$ is the spectral power distribution of the illuminator, $\tau(\lambda)$ is the object spectrum, and $\bar{x}(\lambda)$, $\bar{y}(\lambda)$, and $\bar{z}(\lambda)$ are the color matching functions of the CIE standard observer. The color matching functions correlate with the spectral sensitivity curves of cones. The constant k is defined by $k=100/\int S(\lambda)\bar{y}(\lambda)\mathrm{d}\lambda$, and λ is wavelength.

The wellknown CIE xyY-color space is determined from tristimulus values using the definitions $x=X/(X+Y+Z)$ and $y=Y/(X+Y+Z)$. A large number of other color coordinate systems have been published but they are generally based on some mathematical transformation of the above mentioned tristimulus values.[1-6] Furthermore, a typical colorimeter, color films and color TV are based on this trichromatic principle. Trichromatic equipments form the simplest group of devices also for color recognition purposes.

In this paper we concentrate mainly to color recognition systems which are independent on trichromatic assumption. We do not concern the human visual system nor the trichromatic color measuring. Color recognition mainly from optical pattern recognition point of view will be the subject of the following few pages.

Matched filtering in the Fourier plane of a lens is well-known optical measuring technique which has mainly been used in coherent optical pattern and character recognition. These methods have recently been expanded to spectral dimension, too. They are shortly described in this paper. Optical incoherent pattern recognition only in the spectral domain will be the subject of the third chapter. Next one method of statistical pattern recognition (Subspace Method) and its optical implementations are represented. This method is especially suitable for spectral type of information, and thus for color recognition and classification. It gives the necessary data to design spatial filters for optical pattern recognition in spectral domain. Finally we represent possibilities to compress the measured spectral data in multispectral imaging by the way, that accurate recovering of the original data becomes possible for later recognition purposes.

2. Matched Filtering and Optical Correlation

Optical pattern recognition is often basing on correlation of an input and reference signal or two input signals. The most widely used optical correlator is the matched spatial filtering system (van der Lugt, 1964), which is schematically represented in **Fig. 1**. The matched spatial filter is constructed as follows. The reference transparency is positioned at the input plane of the Fourier transform lens L1. The interference pattern of the Fourier transform of the reference image and a plane reference wave is recorded to a film (reference wave is not seen in **Fig. 1**).

After development, the matched spatial filter is repositioned at the Fourier plane, and an input image transparency is placed in the input plane. Using a second Fourier transform lens L2, the correlation signal of the input pattern and the reference pattern may be obtained in the output plane.

For details of the above described frequency plane correlator and 12 other correlator architectures see Casasent's article in Ref. 7). These and the majority of all other correlation systems are based on use of coherent light and recognition of spatial similarities between an input and reference pattern. They operate only in a monochromatic mode. However, there exists investigations on polychromatic and noncoherent correlators able to manipulate spectral information (color), too. Some of the most important are briefly reviewed in the following.

Case[8)] proposed a wavelength-multiplexed matched spatial filter for color-coded pattern recognition. The idea is to record several spatial filters to a same photographic plate using different coherent wavelengths for each reference patterns. Placing this filter to a coherent optical correlator allows a way to simultaneous recognition of several different objects. In principle, a large number of matched spatial filters can be superimposed onto a same photographic plate, and a white light illumination could be used in the recognition phase. The wavelength-multiplexed spatial filters are more difficult to produce than single exposure filters, but they do not require sequential accurate positioning as a series of usual matched filters.

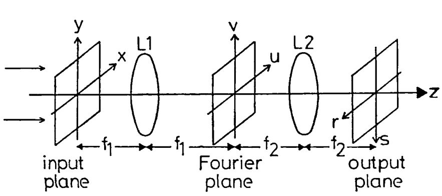

Fig. 1 Optical system for matched spatial filtering.

Yu *et al.*[9)] proposed a spatial encoding technique, where a spatially encoded black and white transparency contains the three primary color information. That is, three different complex spatial filters are spatially multiplexed to a monochromatic film. The three primary color filters must also be used in front of the corresponding complex filters to avoid color cross talk.

Recently Yu[10)] introduced an interesting matched filtering technique for a polychromatic coherent optical correlator. A diffraction grating is placed in the input plane of the basic optical system in **Fig. 1**, and the input transparency is inserted at the front of the grating. Three collinear coherent sources (red, green and blue) form the polychromatic light source. Using a proper diffraction grating it is possible to spatially separate the three color Fourier patterns in the Fourier plane. Several spatial filters for various color images can be sequentially exposed to the same photographic plate by rotating the diffraction grating in the input plane. Compared to wavelength-multiplexing[8)] this spatial multiplexing leads to higher diffraction efficiency and avoids color cross talk.

One drawback of the above mentioned correlation techniques is that the out-of-plane and in-plane alignment errors of the matched spatial filters must be very small. Mu *et al.*[11)] proposed a Fresnel-holographic filter method, where the out-of plane alignment error can be several millimeters, and the correlator is independent on the in-plane shift. Moreover, the diffraction efficiency reaches the value 40%, the system is lensless and there are no color cross talk.

We may think that the above mentioned methods are only expansions of the coherent optical matched filtering technique from the spatial domain to the spectral-spatial domain. Incoherent white light illumination has not actually been applied, although it is in principle possible in some systems. Futhermore, in all experiments the color of the samples has been completely different. So, the color discrimination accuracy of these systems has not yet been investigated.

An interesting trichromatic incoherent optical correlator technique was introduced recently.[12] A statistical pattern recognition algorithm was applied to each three primary colors sequentially using a monochromatic CRT as a light source, and parallely using a color TV monitor as a light source. Design procedures for optical recognition filters were also given. The authors showed clearly that the power of their classification algorithm increases remarkable when spectral-spatial filters were used instead of spatial filters. This is a good example on the importance of spectral information in image analysis.

3. Optical Pattern Recognition in Spectral Region

Spatial filtering and optical processing are still possible, although broad band white light sources are used. Then the filters are not complex filters as in coherent optical processing but simply absorption masks. That is, the dispersed input radiation is transmitted selectively through absorbing filters before detection. This principle actually forms the basis for dispersive correlation spectroscopy.[13,14]

This same filtering idea may be applied to color spectra, too. Caulfield and Mueller[15] used a grating to form spatial spectral distributions of the light signal under investigation. The spectra were then filtered by passing them through a mask and the throughoutput was focused by a lens for detection. Using linear discriminants the authors were able to separate three Kodak filters from each other, although these filters (47, 47A, 48) have almost the same color (blue). Designing discriminant filters, interference filters may also be used instead of absorption masks.[16]

Many mathematical methods familiar in statistical pattern recognition can be applied in filter design for incoherent white light optical processing. One of them, and its optical implementations are described more detailed in the following. We will show how to design optical recognition filters using the Subspace Method,[17] and give some experimental evidence of the power of the algorithm in noncoherent optical pattern recognition and classification.

4. Subspace Formalism

Suppose for a moment that we have the following color recognition problem. We have two sample classes, both of which are known to contain many samples but the color-differences between the samples are small. However, we know that each of the samples belong to one of the two classes. Futhermore, we have a third sample class, where the classification of each sample is unknown, and to be determined. These unknown samples may belong to one of the two known classes, or then to some other class. This is a typical color recognition problem, where the subspace methods may be applied.

Since the subspace formalism in statistical pattern recognition is reviewed in detail elsewhere,[17] only the most central notations are given here.

Each of the observed reflectance, transmittance or radiance spectra (the color signal) is recorded as a set of n wavelengths $\lambda_1, \lambda_2, \cdots, \lambda_n$. Thus a measured spectrum $\tau(\lambda)$ may be interpreted as a vector

$$\tau=[\tau(\lambda_1), \tau(\lambda_2), \cdots, \tau(\lambda_n)]^{\mathrm{T}} \qquad (1)$$

where T denotes the vector transpose. τ is a vector in n-dimensional pattern space R^n. For instance sampling a spectrum at 5 nm intervals from 400 to 700 nm produces a 61 dimensional vector.

According to the subspace formalism we try to find for each class a much lower dimensional subspace as the dimension of the original pattern space. A set of linearly independent vectors $\{v_1, v_2, \cdots, v_p\}$, where $v_i=[v_i(\lambda_1), \cdots, v_i(\lambda_n)]^{\mathrm{T}}$, spans a p-dimensional subspace

$$L=L\{v_1, v_2, \cdots, v_p\}=\left\{x \,\middle|\, x=\sum_{i=1}^{p} a_i v_i\right\} \qquad (2)$$

where a_i are scalars.

Assume we have K classes $\omega^{(1)}, \cdots, \omega^{(K)}$, Our mathematical model for each class is a subspace. These subspaces, $L^{(1)}, \cdots, L^{(K)}$, have the dimensions $p^{(1)}, \cdots, p^{(K)}$. Now, any vector τ has a projection

$$\tau'=\sum_{i=1}^{p}(\tau^{\mathrm{T}} v_i) v_i \qquad (3)$$

to a p-dimensional subspace L. This equation is a linear combination of the basis vectors, vector v_k being weighted by the inner product between τ and v_k. For some parallel optical purposes Eq. (3) may be rewritten as

$$\tau'=\sum_{i=1}^{p}(v_i v_i^{\mathrm{T}})\tau=P\tau \qquad (4)$$

where P is the projection matrix on L. The distance between L and τ is defined by

$$\delta(\tau, L)=\{\|\tau\|^2-\sum_{i=1}^{p}(\tau v_i)^2\}^{1/2} \qquad (5)$$

as usual Euclidean distance. Calculating the distance of τ from all subspaces, τ is classified to the class where the corresponding subspace distance is shortest. Thus the classification rule is

if $\delta(\tau, L^{(i)})<\delta(\tau, L^{(j)})$ for all $j\neq i$ (6)
then τ belongs to the class $\omega^{(i)}$

Once the basis vectors of each subspace are known, we only need to measure the inner products between a spectum and the basis vectors. The basis vectors are n-component vectors, and they may be transformed to optical spatial filters for example in terms of density variations.

There are many methods to construct the subspaces,[17] and the performance of the formalism can be improved by learning.[18] The learning subspace method is basing on associative mappings introduced by Kohonen,[19] and the idea is a decision-directed rotation of the subspaces. This LSM algorithm has been further developed into the average learning subspace method (ALSM).[20]

5. Optical Subspace Classifiers

The above described method applied to color classification offers remarkable simplifications for spectum measurement because absolute spectra are not needed. The spectral distribution of the measuring system can be directly used without taking into account the spectral distribution of the illuminator nor the detector.

The learning subspace methods were used in Ref. 21) to classify white color samples. The samples were indistinguishable by usual chromaticity measurement and almost indistinguishable by visual inspection. Using only three basis vectors for each class subspaces, all fifty-four spectra were correctly classified with aid of the ALSM algorithm.[20] Other classification and clustering experiments of color samples are given in Refs. 22–24).

Figure 2 shows a schematic drawing of a fast acousto-optical subspace classifier.[25] This equipment offers a rapid way to measure both transmission and reflection type of color spectra. Only a single detector is needed, because during the scanning each wavelength is diffracted to a fixed angle. The diffraction efficiency may be controlled by controlling the input electric power of the rf-wave.

The system in **Fig. 2** may be used both to the

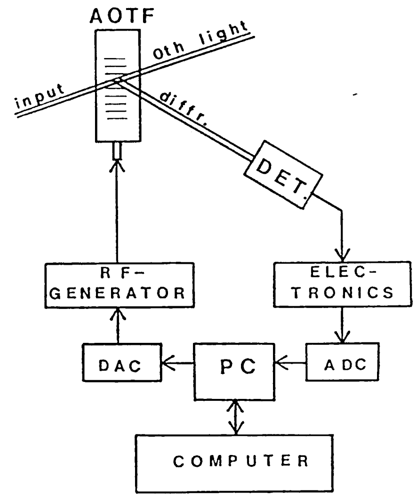

Fig. 2 An acousto-optical color recognition system.[23]

learning phase and the recognition phase of subspace classification. In the learning phase the known samples, the training set, are measured and the subsequent subspaces for each class are determined using the computers belonging to the equipment. Then the basis vectors of the subspaces are stored to the microcomputers memory. For instance, if four three-dimensional classes are used, twelve basis vectors must be stored. In the recognition phase Eq.(3) is used to determine the projections of a measured spectra to each subspace and finally the measured sample is classified using a classification rule as Eq. (6). All computations are so simple, that the recognition phase is the faster, the faster is the spectrum measurement. The calculations of the recognition phase may also be performed during the scanning by adjusting the diffraction efficiency of the grating according to the basis spectra information.

Another parallel optical subspace computer is shown in **Fig. 3**. The object light is dispersed using a grating and a sylindrical lens. The spectrum is manipulated in the filter plane by a spatial filter array and then focused to detectors by another cylindrical lens. In the learning phase a row detector, for example CCD, is placed to the filter plane and the basis for the subspaces are determined. Then the basis vectors are coded to transmittance variations on a film, and the filter is placed to the filter plane for color recognition and classification. Using a 2D-spatial light modulator in the filter plane, both the learning phase and filter coding may be done quickly.

Similarly as in Ref. 15) the system in **Fig. 3**

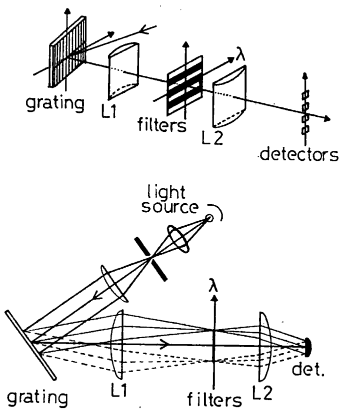

Fig. 3 A parallel optical color recognition system.

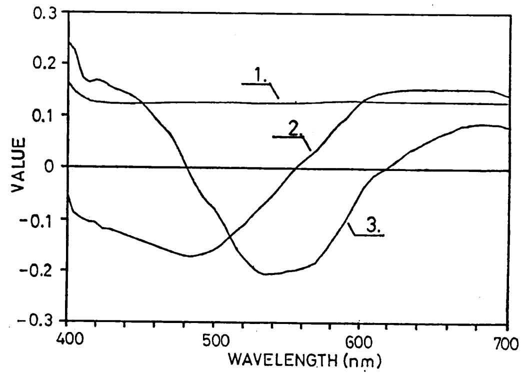

Fig. 4 The first three characteristic spectra of a large database containing 1257 surface reflectance spectra.[29]

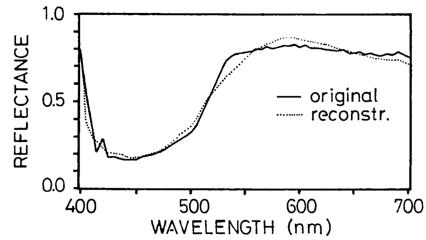

Fig. 5 Reconstruction (dotted line) of a measured spectrum (solid line) using four characteristic spectra of the 1257 surface reflectances. Sampling interval was 5 nm.

is using a white light source and operating only in the spectral domain.

6. Spectral Representation of Colors

For general purpose color recognition trichromatic measuring systems are generally used. However, in machine vision it is unnecessary to restrict to trichromatic systems if we are able to compress the spectral data by the way that preserves most of the spectral information.

Typical color spectra of natural samples have a smooth shape instead of consisting of a set of narrow band peaks. This means that the spectra are strongly correlated, and may consequently be represented as a linear combination of few characteristic spectra (also called as principal spectra, basis spectra, eigenspectra and component spectra). Principal component analysis (PCA) is one of the most common tools to analyse spectral information. PCA has been used to show, that three characteristic spectra are enough to represent daylight,[26,27] and depending on the accuracy requirements, 5-8 characteristic spectra lead to essentially perfect recover of surface reflectances.[28,29]

To the author's knowledge the largest set of surface spectral reflectances in the visible part of the spectrum has been analysed in Ref. 29). The color data was collected measuring 1257 reflectance spectra of the chips in the Munsell Book of Color. The characteristic vector decomposition and some reconstructions were given. The three most significant characteristic spectra are shown in **Fig. 4**, too. The ability of these vectors to explain overall variance of the data set is about 98%. Using four characteristic vectors increases the information contents by 1%. Because the characteristic vectors are orthogonal, this means remarkable data compression: All spectra may be represented in a four-dimensional subspace. Thus using Eq. (3), measuring only four inner products $\tau^T v_i$ give possibility to reconstruct the original spectrum. For object colors four-dimensional representation is generally sufficient, although sometimes higher dimensional subspaces are needed, too. An example of the reconstruction power of the Munsell basis is shown in **Fig. 5.**

The Munsell basis is also capable to reconstruct natural colors, although a bit higher dimemsional subspaces are needed.[30] Moreover applied to multispectral imaging, it is possible to find such three component representation (same memory requirements as RGB image has), that the original color spectra can be reconstructed with good accuracy for each image pixel.[30]

7. Conclusions

The traditional coherent optical correlators with matched filtering technique have recently been expanded to spectral-spatial domain, too. However, they are still basing on use of laser sources, even though there are growing interest in incoherent optical processing. Color discrimination accuracy of the spectral-spatial correlators has not yet been investigated. On the other hand spatial filtering technique for incoherent spectral pattern recognition has been applied more than 20 years but systematic methods of filter design have not been studied until recently.

Digital image processing and pattern recognition offers efficient mathematical methods, which may often be realised optically, too. One method, discussed in this paper, is The Learning Subspace Method of classification. It has been shown by unsupervised learning experiments that this model will adapt itself to the structure of the color space. Furthermore, using a standard analog-optical vector-matrix multiplication scheme, optical realisations for many color recognition purposes may be constructed. Finally, using a well designed single subspace, color recognition possibilities of machine vision can be improved and expanded, because instead of a standard trichromatic color representation, whole color spectra can be connected to each image pixel without significantly increasing the computer storage requirements.

References

1) A. R. Robertson: "The CIE color difference formulae," Color Res. Appl., **2** (1977) 7.
2) R. D. Lozano: "Evaluation of different color-difference formulae by means of an experiment on color scaling," Color Res. Appl., **2** (1977) 13.
3) T. Benzschawel and S. L Guth: "ATDN: toward a uniform color space," Color Res. Appl., **9** (1984) 133.
4) R. M. Boynton, A. L. Nagy and C. X. Olson: "A flaw equation for predicting chromatic differences," Color Res. Appl., **8** (1983) 69.
5) D. C. Rich and W. Billmayer, Jr.: "Small and moderate color differences IV, color-difference perceptibility ellipses in surface color space," Color Res. Appl., **8** (1983) 31.
6) D. L. MacAdam: "Uniform color scales," J. Opt. Soc. Am., **64** (1974) 1691.
7) D. Casasent: "Pattern and character recognition," *Handbook of Optical Holography*, Ed. H. J Caulfield (Academic Press, 1979).
8) S. K. Case: "Pattern recognition with wavelength-multiplexed filters," Appl. Opt., **18** (1979) 1890.
9) F. T. S. Yu, T. H. Chao and S. L. Zhuang: "Polychromatic processing technique for color image transparencies," Appl. Opt., **19** (1980) 1887.
10) F. T. S. Yu: "Color image recognition by spectral, spatial matched filtering," Opt. Eng., **23** (1984) 691.
11) G. G. Mu, D.-Q. Chen and Z.-Q. Wang: "Color-image correlation with a multiwavelength Fresnel holographic filter," Opt. Lett., **13**, No. 6 (1988) 434.
12) Z.-H. Gu, S. H. Lee and Y. Fainman: "Statistical recognition of color images," Appl. Opt., **26** (1987) 3145.
13) M. M. Millan and R. M. Hoff: "Dispersive correlation spectroscopy: a study of mask optimization procedures," Appl. Opt., **16** (1977) 1609.
14) R. B. Kay: "Absorption spectra apparatus using optical correlation for the detection of trace amounts of SO_2," Appl. Opt., **6** (1967) 776.
15) H. J. Caulfield and P. E. Mueller: "Direct optical computation of linear discriminants for color recognition," Opt. Eng., **23** (1984) 16.
16) Y. Fainman, S. H. Lee and A. R. Johnston: "Color filters for multispectral image identification and separation," J. Opt. Soc. Am. A, **1** (1984) 1302.
17) For detailed description of subspace methods see: E. Oja: *Subspace Methods of Pattern Recognition* (Research Studies Press, Letchworth, 1983).
18) T. Kohonen, G. Nemeth, K.-J. Bry, M. Jalanko and H. Riittinen: "Spectral classification of phonemes by learning subspaces," Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Processing, Washington (1979) pp. 97-100.
19) T. Kohonen: *Self-Organization and Associative Memory*, 2nd ed. (Springer-Verlag, Berlin, 1988).
20) E. Oja and M. Kuusela: "The ALSM algorithm—an improved subspace method of classification," Patt. Recog., **16** (1983) 421.
21) J. Parkkinen and T. Jaaskelainen: "Color representation using statistical pattern recognition," Appl. Opt., **26** (1987) 4240.
22) J. P. S. Parkkinen, T. Jaaskelainen and E. Oja: "Pattern recognition approach to color measurement and discrimination," Acta Polytech. Scand. Appl. Phys. Ser., **7** (1985) 171.
23) T. Jaaskelainen, J. Parkkinen and E. Oja: "Color discrimination by optical pattern recognition," *Proceedings of 8th International Conference on Pattern Recognition*, Paris (1986) pp. 766-768.
24) J. Parkkinen, E. Oja and T. Jaaskelainen: "Color analysis by learning subspaces and optical processing," *Proceedings of IEEE 1988 Int. Conf. on Neural Networks*, San Diego (1988).
25) J. Hallikainen, J. Parkkinen and T. Jaaskelainen: "An acousto-optic color spectrometer," Rev. Sci. Instrum., **59** (1988) 81.
26) D. B. Judd, D. L. MacAdam and G. Wyszecki: "Spectral distribution of typical daylight as a function of correlated color temperature," J. Opt. Soc. Am., **54** (1964) 1031.
27) E. R. Dixon: "Spectral distribution of Australian daylight," J. Opt. Soc. Am., **68** (1978) 437.
28) L. T. Maloney: "Evaluation of linear models of surface spectral reflectance with a small number of parameters," J. Opt. Soc. Am. A, **3** (1986) 1673.
29) J. Parkkinen, J. Hallikainen and T. Jaaskelainen: "Characteristic spectra of Munsell colors," J. Opt. Soc. Am. A, **6**, Feb. (1989).
30) J. Parkkinen, T. Jaaskelainen and M. Kuittinen: "Spectral representation of color images," *Proceedings of the 9th Int. Conf. on Pattern Recognition*, Roma (1988).