Neural Networks in Two Cascade Algorithms for Spectral Reflectance Reconstruction

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Abstract— **In this paper, we deal with the problem of the spectral reflectance curves reconstruction. Because of the reconstruction of such curves is an inverse problem, slight variations in input data completely skew the expected results. So, finding a robust reconstruction operator is highly required. We present a robust method based upon neural networks. This method takes advantage of that neural networks are generally robust to the noise. Furthermore, we propose two cascade algorithms of using these neural networks. The first algorithm allows faithful reconstruction of spectra that are previously learned. The second algorithm allows good generalization allowing for reconstructing a wide range of reflectance that are not learned in the training stage. The results confirm the robustness and the reliability of the proposed method compared to some classical ones.**

Keywords: multispectral imaging ; spectral reflectance; neural networks; cascade algorithms

I. Introduction *(Heading 1)*

Conventional color imaging defines each pixel with 3 variables such as red, green and blue, which are necessary and sufficient to characterize any color. This principle, the three dimensionality of color, has several limitations. First, in a color image acquisition process, the scene is acquired using a given illuminant. So, it is impossible to estimate the scene color under another illuminant. Moreover, two color samples can match under one illuminant and appear completely different under another illuminant. This phenomenon is called metamerism. Multispectral imaging systems remedy these problems by increasing the number of acquisition channels. In doing so, multispectral imaging presents the advantage of high spectral resolution over classical color imaging systems and the advantage of high spatial resolution over spectrophotometers. Such system has the potential to recover the spectral reflectance of the scene surface from the camera output. However, finding appropriate mathematical methods to estimate the spectral reflectance of a scene from the camera output is a crucial task and of great importance. Several methods to achieve this task exist in literature [1-3]. Some classical approaches use the pseudo-inverse calculus and the least squares. The main drawback of these methods is the noise amplification. Some other methods seek to maximize the smoothness of the estimate result [4, 5]. Another reliable method proposed in [6] takes advantage of the *a priori* knowledge on the spectral reflectances that are to be imaged. We can also cite another method using a mixture density network [7].

In this paper, we introduce a robust method for spectral reflectance estimation based upon neural networks: associative memories. We propose the use of these memories in two cascade algorithms. Each of these configurations is adapted to a specific situation but both present the advantage to be robust to noise. In Section 2 we present the multispectral system we use. Then we explicit, in Section 3, the spectral model we adopt. In Section 4, we formulate the problem of spectral reflectance recovery using neural networks. Some results are given and commented on in Section 5. Then, we conclude in Section 6.

II. Multispectral Imaging System

In our laboratory we developed a multispectral camera with a rotating wheel. This system is composed of a single CCD-based camera, and a set of 10 interference filters. A wheel equipped with 10 holes houses, akin to a rotary telephone dial, the 10 filters. The wheel is located in front of the camera/lens system. It is motorized to rotate, and all is piloted by software. A multispectral image is acquired during each revolution and transferred to the computer (see "(Fig. 1)"). With such a system we seek to reconstruct data representing the spectral reflectance in each pixel of the imaged scene. This reconstruction is an inverse problem. That means that a slight error in data completely skews the expected results. To avoid this, the system must be calibrated in order to have images of high quality. Thus, a pre-processing of the acquired channel-images is required. We developed a channel-adapted protocol to reduce noise in such system [8]. It allows correction of the offset and the thermal noises, the gain difference between CCD cells, and the non-linearity of the camera response.

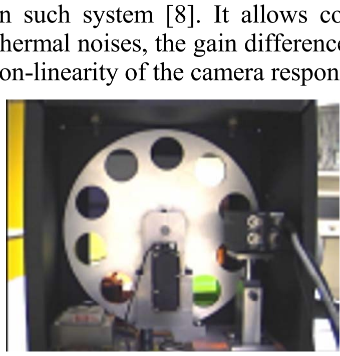

Figure 1. The multispectral system we use. It is based on monochromatic camera and a set of 10 interference filters.

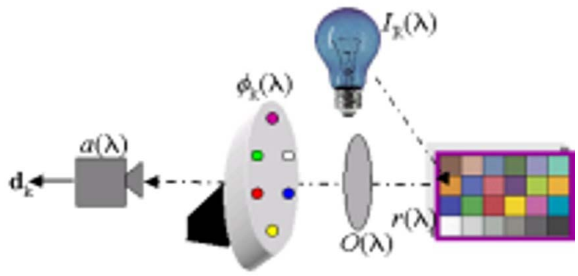

Figure 2. Synopsis of the spectral model of the acquisition process in a multispectral system.

III. Spectral Model Of Acquisition

The components involved in the acquisition process in a multispectral imaging system are illustrated in the "Fig. 2" where I(λ) is the spectral radiance of the illuminant, r(λ) is the spectral reflectance of the surface, o(λ) is the spectral transmittance of the optical system, $\phi_k(\lambda)$ is the spectral transmittance related to the k^{th} filter and a(λ) is the spectral sensitivity of the camera. The camera output d_k, related to the channel k for a single pixel of the image, is given by "(1)":

$$d_k=\int_{\lambda_{min}}^{\lambda_{max}} I(\lambda)r(\lambda)o(\lambda)a(\lambda)\Phi_k(\lambda)d\lambda \,. \quad (1)$$

Supposing a linear opto-electronic transfer function, we can replace $I(\lambda)$, $a(\lambda)$, $o(\lambda)$ and $\phi_k(\lambda)$ by the spectral sensitivity $\mathbf{S}_k(\lambda)$ of the k^{th} channel. Then, the Equation (1) becomes:

$$d_k=\int_{\lambda_{min}}^{\lambda_{max}} r(\lambda)S_k(\lambda)d\lambda \,. \quad (2)$$

By sampling the spectra to N wavelengths, "(2)" can be written in matrix notations as in "(3)"

$$d_k=\mathbf{r}(\lambda)^T\mathbf{S}_k(\lambda). \quad (3)$$

$S_k(\lambda)=[s_k(\lambda_1)\ s_k(\lambda_2)\ldots\ s_k(\lambda_N)]^T$ is the vector containing the spectral sensitivity of the acquisition system related to the k^{th} channel, $\mathbf{r}(\lambda)=[r(\lambda_1)\ r(\lambda_2)\ldots\ r(\lambda_N)]^T$ is the vector of the sampled spectral reflectances of the scene. ^{T} is the transpose operator.

From "(3)", we first search to characterize the spectral response of the system, including the camera and the illuminant, by finding the operator $\mathbf{S}_k(\lambda)$. Then, using this operator, we reconstruct, from a multispectral image, the spectral reflectance curve for each pixel of the imaged scene.

IV. Problem Formulation

A. *Definition*

Artificial neural networks simulate the behavior of many simple processing elements present in the human brain, called neurons. Each neuron is linked to each other by connections called synapses. Each synapse has a coefficient that represents the strength or weight of the connection. Learning or training is accomplished by adjusting these weights to cause the neural network to appropriate output results. The learning rules specify how to calculate the modification of the weights based on the objective. The perceptron illustrated in "(Fig. 3)" is the first and basic model of existing neural networks [9].

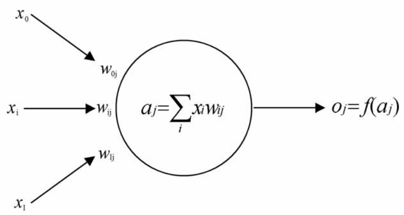

Figure 3. One output cell of a perceptron.

a_j is the activation of the j^{th} output cell, x_i is the answer of the i^{th} input cell and w_{ij} is the intensity connection between i^{th} input cell and j^{th} output cell. The answer o_j of the j^{th} output cell, which is function of the neuron activation a_j, is only 0 or 1 in the case of deterministic perceptron.

Because the perceptron gives the same response to the same stimulus after training, we modify its behavior by modifying the function f that translates the activation into a response. In our case, we have used the Boltzmann distribution. The perceptron gives now probabilistic response. This option corresponds to the creation of associative memories. Associative memories can be heteroassociative or autoassociative. Heteroassociative memories associate a stimulus in the input to a response in the output even if the two vectors have not the same size, where autoassociative memories (particular case) associate a stimulus to itself and can, thusly be used to store stimuli. A statistical reason for which we use a probabilistic response is that: during the training, the perceptron may learn only few samples among possible stimuli. The memory stops learning when it ceases to mistake any more. So, it may place the discriminating function too much close to the boundaries of the samples with which it was trained. Now, if we test it on new samples coming from the same statistical population, the perceptron badly generalizes its training. In this way, as rule of training, we use the Delta rule also known as Widrow-Hoff rule [10]. This rule is based on the idea of continuously modifying the strengths of the input connections to reduce the difference (the delta) between the expected output value e and the actual output o of a neuron. This rule changes the connection weights in the way that minimizes the mean squared error of the neuron between an observed response o and a desired theoretical one like:

$$w_{ij}^{t+1}=w_{ij}^{t}+\eta(e_j-o_j)x_i=w_{ij}^{t}+\Delta w_{ij} \quad (4)$$

where e is the expected response, t is the number of iteration, and η is a learning rate.

B. *Experiments*

Since the goal is to work out the spectral sensitivity of our system for each channel, we learn to the system a set of patches from the Macbeth[1] color checker where the reflectances are

[1] GretagMacbeth Color Checker, 1998.

well known, and by observing the camera responses, we can characterize our system from the "(3)". To do this, we have scanned the Macbeth chart using a Minolta CS-1000 spectrophotometer and we acquire a multispectral image of this chart. We now know the spectral reflectance curves of the set of the *P* patches and we have an image of these patches with the multispectral camera, then we have a set of corresponding pairs ($\mathbf{d}_p$, $\mathbf{r}_p$), for p=1,...,*P*, where $\mathbf{d}_p$ is a vector of dimension K=10 containing the camera output and $\mathbf{r}_p$ is a vector of dimension *N* representing the spectral reflectances of the p^{th} patch. In our case, *N* is equal to 80 and represents the sampling of the visible range of the light from 380 nm to 780 nm by a step of 5 nm. The reflectances $\mathbf{r}_p$ of the *P* patches are stored in a matrix we call **R** of size *N***P*.

B. Spectral Reflectance Reconstruction

Associative memories meet our needs because we want to associate an input vector corresponding to the *K* gray-level values of a pixel to an output vector representing the spectral reflectance sampled *N* values. From "(3)", we can see the problem like that: we search a set of values of w_{ij} such that the memory associates a configuration on the *N* output cells with stimuli presented in the *K* input cells (corresponding to *k* channels) of the neural network. The memory associates a vector of *K* values coming from the multispectral image to a vector of *N*=80 values. In matrix notation, we express this as finding a matrix of weight **W** of order *N* **K* with:

$$e_p=o_p=W^T x_p \quad (5)$$

e_p is the vector containing the expected response, x_p is the vector containing the input values coming from the multispectral image (*k* values), and o_p is the output for the stimulus *P*. In the first time, we determining **W** corresponds to learning which lead to determining the system response **S** for all the *K* channels. The second step is the reconstruction. Since all weighted synapses are gathered in a matrix, the reconstruction is fast and easy: the estimated spectral reflectance $\mathbf{r}(\lambda)$ in each pixel of a scene is equal to a product between this matrix and the camera response. This operation is easy and trivial in the case where *k*=*N*. However, practically, it does not hold because it is difficult to provide a number of channels equal to the rate of sampling the spectra using a rotating wheel. That is why we use several memories in cascade algorithm to overcome this limitation.

1) First Algorithm:

In this algorithm we use twice one autoassociative memory and one heteroassociative memory like in "(Fig. 4)". The first autoassociative memory is used to store the reflectances contained in **R** during training. The hétéroassociative memory reconstruct an intermediate response $\mathbf{r}_i$ of size N*P from the camera output $\mathbf{d}_k$ of size K*P. Then, the same autoassociative memory filters this vector $\mathbf{d}_k$ with the stored stimuli to reconstruct the final reflectance **r**. This is possible because of an interesting property, remarked by Kohonen [12], of the

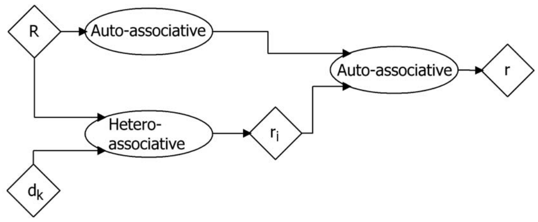

Figure 4. First cascade algorithm for spectral reflectance reconstruction.

autoassociative memories. This property consists of their capacity to recover an information previously stored using only a part of this information which is called key. The result of this operation depends on the key information given to recover the real stored information. In our case, we use intermediate reflectances $\mathbf{r}_i$ as key. This algorithm seems to be similar to a multilayer neural networks. However, we found, experimentally, that the proposed algorithm gives quite superior results than a memory with hidden layers. lace figures and tables at the top and bottom of columns. Avoid placing them in the middle of columns.

2) Second Algorithm

In this algorithm, we use two heteroassociative memories like in "(Fig. 5)", one downstream from the other. The first heteroassociative memory, knowing **R**, reconstructs an intermediate response $\mathbf{r}_i$ (*N***P*) from the camera output $\mathbf{d}_k$ (*K***P*). Then, the second heteroassociative memory relays $\mathbf{r}_i$ to reconstruct final **r** knowing **R**. The second heteroassociative memory must have a different function that translates activation into response. This algorithm is robust for a better generalization. Indeed, this method has the potential to reconstruct spectra which were not learned under condition of belonging to the same statistical population. We note that the larger and more representative **R** is, better the generalization is.

V. RESULTS

To evaluate the method based on the first algorithm, we have chosen to compare spectral reflectance estimation for all of the Macbeth patches. The methods involved in comparison are pure pseudo-inverse and the *a priori* one [6]. The "(Fig. 6)" shows an instance of estimation: we can clearly see that the pseudo-inverse method is bad and not acceptable; the *a priori* method gives as good results as the method we propose.

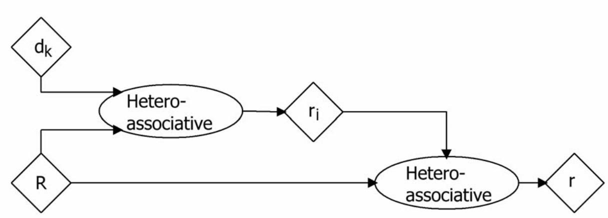

Figure 5. Second cascade algorithm for spectral reflectance reconstruction.

We can notice the fact that the spectrum reconstructed by the proposed method is smoother than other methods. This is verified for all estimation we made. It comes from the property of the neural network which are robust to noise. In terms of quantitative metric, we calculate the Goodness-of-fit Coefficient (GFC) defined as:

$$GFC = \frac{\left|\sum_j R_m(\lambda_j) R_r(\lambda_j)\right|}{\left(\left|\sum_j [R_m(\lambda_j)]^2\right|\right)^{1/2} \left(\sum_j [R_r(\lambda_j)]^2\right)^{1/2}} \quad (6)$$

where $R_m(\lambda_j)$ is the value measured by the spectrophotometer in the wavelength λ_j, and $R_r(\lambda_j)$ represents the reconstructed value related to the same wavelength. For these 3 methods – pseudo-inverse, *a priori*, and neural network ones – and, for all the patches, we found an average of, respectively: 72.44 %, 98.40 % and 99.55 %. From these results the proposed method delivers the best performance.

In order to test the reliability of the method based on the second algorithm, we scanned with the spectrophotometer a patch coming from a chart other than Macbeth but which belongs to the same statistical population. Afterwards, we acquire it by the multispectral camera. We reconstruct the spectral reflectance using the *a priori* method and the proposed one according to the second algorithm. Results are shown in "(Fig. 7)" and "(Fig. 8)". Spectra reconstructed using neural networks match better with theoretical one. The generalization is satisfactory.

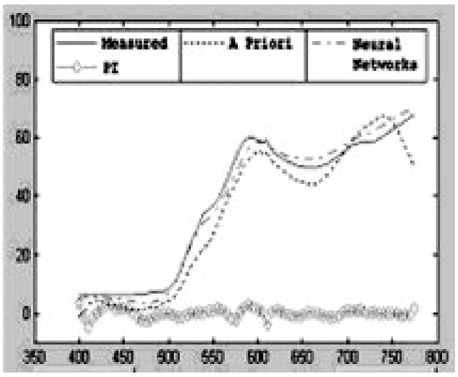

Figure 6. Comparison between measured spectral reflectance of the 12th patch of the Macbeth chart and reconstructed spectra using three methods.

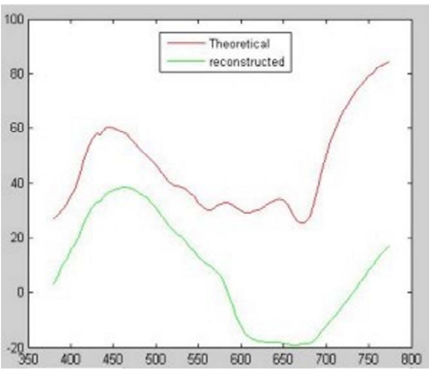

Figure 7. Reconstructed spectral reflectance using *a priori* method

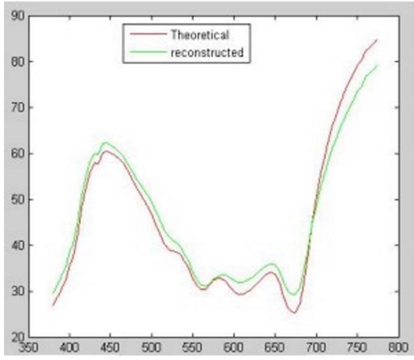

Figure 8. Reconstructed spectral reflectance using associative memories (second algorithm).

VI. CONCLUSION

We have presented in this paper a method for spectral reflectance reconstruction from multispectral images. This method is based upon neural networks. We formulated the problem of spectral reflectance reconstruction using hetero-associative memories. The architecture of this neural network and the rule of training were explicated. We gave some results showing the best performance of this method over classical others. This method has also the advantage to correctly reconstruct some reflectances that are not being learned since they belong to the same statistical population. We now aim to apply this method for real applications with reflectances of different structures.

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