Spectral Ordering Assessment Using Spectral Median Filters

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Abstract. Distance-based mathematical morphology offers a promising opportunity to develop a metrological spectral image processing framework. Within this objective, a suitable spectral ordering relation is required and it must be validated by metrological means, e.g. accuracy, bias, uncertainty, etc. In this work we address the questions of suitable ordering relation and its uncertainty for the specific case of hyperspectral images. Median filter is shown to be a suitable tool for the assessment of spectral ordering uncertainty. Several spectral ordering relations are provided and the performances of spectral median filters based on the aforementioned ordering relations are compared.

Keywords: Spectral ordering · Median filters · Mathematical morphology

1 Introduction

Taking the benefits of its discriminating power that goes beyond color or grayscale imaging, more and more application fields explore the possibilities offered by hyperspectral imaging [7,10,16]. Unfortunately, the advances in image processing does not quite follow the imaging technology. Regardless of the vast amount of data contained in a hyperspectral image, most of the processing requires either dimensionality reduction or band selection so as to make processing with the existing operations possible [17,19]. Considering such amount of data, using data reduction approaches is indeed understandable. However, such approaches negate the initial purpose of using hyperspectral images, i.e. to improve accuracy by acquiring and processing more information. With that reason, the focus of this work is to process hyperspectral data in vector and full-band approach.

Hyperspectral data are not basic mathematical objects, they are physical measures of energy or percentage of energy across the wavelengths. Due to the mathematical and physical nature of hyperspectral images, there is no valid addition, multiplication by scalar value, and subtraction operations available for such data. Fortunately, as it is possible to define and validate distance measure between hyperspectral data [8], it is also possible to define ordering relation based on distance function [12].

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The article is organized as follows. First, we consider in Section 2 the questions regarding the ordering of spectral data, and then we propose some basic ordering relations linked to the particular structure of a spectrum. Then we develop the questions around the quality assessment of ordering relation for spectral data in Section 3. The result and discussion of using spectral median filters to assess the quality of spectral ordering relation is provided in Section 4.

2 Hyperspectral Ordering

Ordering relation is the core of many important image processing tools, e.g. mathematical morphology and rank order filters. While natural order exists in scalar domain [5,11], ordering in vector or multivariate case is ambiguous and many different approaches of multivariate ordering exist [2,4,18]. Furthermore, when constructing an ordering, the nature of the data at hand needs to be taken into account as opposed to only considering them as mathematical objects. Hyperspectral data is defined a sequence of energy measured on spectrally contiguous channels where each channel is defined with a certain bandwidth. This basic definition of hyperspectral data then leads to the digitization of a continuous energy spectrum across the wavelengths and, as a consequence, a spectrum is neither a vector in Euclidean space nor a distribution [8]. In this work, the studied hyperspectral data are represented in terms of spectral reflectance and were acquired in the visible and near-infrared spectral range. In reflectance space, each measure is a ratio of the acquired energy divided by the illuminant energy of the corresponding spectral band. Nevertheless, the purpose can be directly extended to other spectral ranges or radiance space.

By respecting the physical definition of a spectrum and considering the ordering constructions proposed by Barnett [4] and further extended to multivariate images by Aptoula [2], several spectral ordering relations are provided in the followings. Given an arbitrary spectrum as a function of wavelength or spectral band λ_p, $S_i = \{S_i(\lambda_p),\ p \subset [0, n-1]\}$, marginal or component-wise ordering approach is as shown in Eq. 1. The main idea is to order a spectrum based on the values of each of its component and to combine logically the result. Due to such construction, this ordering is not able to order all spectra, e.g. when $S_1(\lambda_{p-1}) < S_2(\lambda_{p-1})$ and $S_1(\lambda_p) > S_2(\lambda_p)$. Moreover, this partial ordering is not able to preserve correlations that exist between neighboring spectral band.

$$S_1 \preceq S_2 \Leftrightarrow \begin{cases} S_1(\lambda_1) \leq S_2(\lambda_1) \text{ and} \\ S_1(\lambda_2) \leq S_2(\lambda_2) \text{ and} \\ \qquad \cdots \qquad\quad \text{and} \\ S_1(\lambda_n) \leq S_2(\lambda_n) \end{cases} \tag{1}$$

Lexicographic ordering is an example of conditional ordering approach; it is a total order. In this approach the ordering is based on conditions or prioritizations applied on each spectral channel, see Eq. 2 where priorities are given to shorter wavelengths and C is an arbitrary constant number. Prioritization over a hyperspectral image with hundreds of channels is challenging since in most of the cases the discriminating channels are unknown, unlike in a color image of typically three channels. Moreover, this construction states that the order of a spectrum is determined by the order of few of its channels, while the rest of the channels will be considered to be almost negligible.

$$S_1 \preceq S_2 \Leftrightarrow \sum_{p=0}^{n-1} C^{n-p} \cdot S_1(\lambda_p) \leq \sum_{p=0}^{n-1} C^{n-p} \cdot S_2(\lambda_p) \tag{2}$$

Considering that a spectrum is an energy, the ordering relation in Eq. 3 is proposed. The underlying hypothesis to this point of view states that a spectrum is considered as 'larger' than another if its total amount of energy is bigger. With this ordering relation, a white spectrum is always 'larger' than a black spectrum. This ordering is in a direct equivalence to morphology based on intensity images.

$$S_1 \preceq S_2 \Leftrightarrow \int_\lambda S_1(\lambda)\, d\lambda \leq \int_\lambda S_2(\lambda)\, d\lambda \tag{3}$$

The previous ordering relation is limited to energy point of view and implicitly defines the convergence of spectral extrema toward the black and white spectra. In the context of color image processing, the notion of distance function has been used to address several image processing tasks [1,14,20]. Using distance function, two spectra can be ordered by their distance relative to a reference spectrum S_{ref} (Eq. 4). If a white spectrum is used as the reference, the behavior obtained from Eq. 4 will be similar to that of Eq. 3 where a spectrum is considered as an energy, i.e. larger spectrum is the one having more energy.

$$S_1 \preceq S_2 \Leftrightarrow d(S_1, S_{ref}) \geq d(S_2, S_{ref}) \tag{4}$$

The two previous ordering relations do not satisfy total ordering property as well as not allowing to fully control the extrema in a morphological process according to certain application goals. Ledoux et al. [13] proposed the Convergent Colour Mathematical Morphology (CCMM) by combining two reference coordinates to control the convergence of the color set toward selected infimum and supremum. This total ordering relation was shown to be suitable for color vector processing such as texture discrimination or pattern detection in a spatio-chromatic template. A preliminary work on hyperspectral images demonstrated that the purpose was extendable to spectral domain [12]. CCMM defines two convergence coordinates $O^{+\infty}$ and $O^{-\infty}$ in order to compute the ordering relation for the maximum and minimum extraction in a set of spectra (Eq. 5).

$$\begin{aligned} S_1 \succeq S_2 &\Leftrightarrow d(S_1, O^{+\infty}) \leq d(S_2, O^{+\infty}) \\ S_1 \preceq S_2 &\Leftrightarrow d(S_1, O^{-\infty}) \leq d(S_2, O^{-\infty}) \end{aligned} \tag{5}$$

The ordering relation of CCMM (Eq. 5) does not satisfy the idempotency property of opening and closing transforms and a construction in which the two distances are expressed in a single relationship is required [9]. Thus, we propose an ordering that uses the ratio between the distance to the reference coordinate for the maximum $O^{+\infty}$ and for the minimum $O^{-\infty}$ (Eq. 6). With this construction, the maximum in set of spectra will be the one closest to $O^{+\infty}$. If several spectra are at the same distance to $O^{+\infty}$, the maximum is the one closest to $O^{-\infty}$ coordinate; this construction ensures idempotency property.

$$S_1 \preceq S_2 \Leftrightarrow \frac{d(S_1, O^{-\infty})}{d(S_1, O^{+\infty})} \leq \frac{d(S_2, O^{-\infty})}{d(S_2, O^{+\infty})} \tag{6}$$

The ordering relation in Eq. 6 does not guarantee a total order as different color or spectral coordinates can produce the same ratio. Thus, additional constraints are required in order to produce a total order, i.e. using a conditional construction as in Eq. 7. In this case, the first part of the relation is identical to that of Eq. 6 and the additional constraint is proportional to a spectral angle.

$$\begin{gathered} S_1 \preceq S_2 \Leftrightarrow \begin{cases} R_0(S_1) \leq R_0(S_2) & \text{or} \\ R_0(S_1) = R_0(S_2) & \text{and} \quad R_1(S_1) \leq R_1(S_2) \end{cases} \\ \text{with } R_0(S) = \frac{d(S, O^{-\infty})}{d(S, O^{+\infty})},\ R_1(S) = 2\frac{d(S, O^{-\infty})}{d(O^{-\infty}, O^{+\infty})} \end{gathered} \tag{7}$$

For n-dimensional data such as hyperspectral images, experiments show that the second relation of Eq. 7 is almost never used. Spectral complexity, acquisition noise, and other factors affecting a spectral data allow to work only with the ordering relation shown in Eq. 6. Such behaviour can be expressed through the mathematical conjecture in Eq. 8, i.e. the probability of obtaining more than one spectral coordinate as the maximum (or minimum) at level R_i of a conditional ordering relation, k being the number of spectral channels.

$$prob\left(\#\left\{\bigcap_{i=1}^{k-1} Sd_i\right\} > 1\right) > prob\left(\#\left\{\bigcap_{i=1}^{k} Sd_i\right\} > 1\right) \tag{8}$$

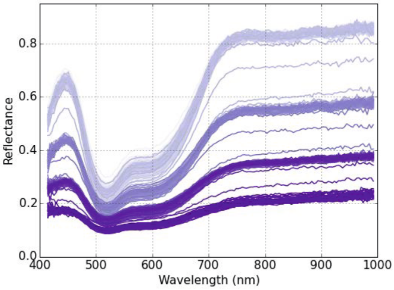
3 Spectral Ordering Accuracy Assessment

3.1 Uncertainty in Color Ordering

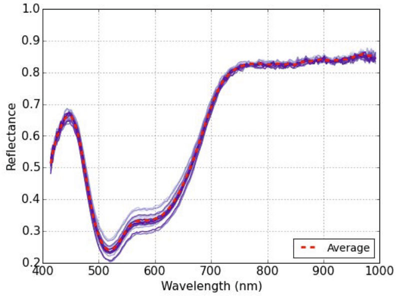
Given a sequence of ordered colors, where each two colors are slightly different by a certain color gradient, any arbitrary ordering relation must be able to retain the initial order of this sequence of colors [15], see Eq. 9. This hypothesis enables a way to assess the uncertainty of color ordering relations. A randomly generated sequence of colors can be obtained by, first, randomly selecting extremal colors and, second, iteratively adding a certain amount of color gradient to the extremal colors so as to obtain the in-between colors. This color ordering uncertainty test is however too restrictive for spectral images. As illustrated by metamerism phenomenon, reducing spectral data into color data might yield identical colors despite the different spectral signatures. And eventually, reducing spectral ordering uncertainty test into color domain loses the meaning of spectral image processing, i.e. to improve accuracy.

(a) A pigment patch

(b) Regions of interest (roi)



(c) Spectral reflectances of roi-1



(d) Spectral reflectances of roi-2

Fig. 1. A pigment patch was acquired using a hyperspectral scanner and its color image was constructed using color matching function. The obtained spectral reflectance signals illustrate how global extrema extraction in roi-1 is a less complex problem than obtaining spectral ordering in a small region such as in roi-2 where the spectra are similar to the average spectrum of this region.

$$\begin{aligned} \exists! C_m \mid C_m = \bigwedge_{i:0\ldots p} C_i = \bigwedge_{i:0\ldots p} R(C_i) \\ \text{and } R(C_{i-1}) > R(C_i), \forall i \leq m \\ R(C_{i+1}) > R(C_i), \forall i \geq m \end{aligned} \tag{9}$$

In order to assess spectral ordering uncertainty, rather a sequence of colors, a sequence of spectra should be generated and the physical definition of a spectrum must be taken into account. Furthermore, a set of spectral images where its ground truth is available must be obtained so as to have a set of data that is close to reality. Unfortunately, there is no such dataset. And even if there is, the problems of ordering will not be encountered when the global extrema, i.e. maximum and minimum, are to be extracted from the dataset. Such is, in fact, less complex than when working with a small-sized structuring element on a region where each of the spectra are similar to the average of this region, where consequently accuracy should be at its maximum. To summarize, spectral ordering is less likely to face a problem at the level of generated uncertainty. Challenges will be encountered at texture feature level where uncertainties are integrated in the data in multiscale construction, see Fig. 1. Finally, the uncertainty of a spectral ordering relation must be assessed within the distribution of input spectral data.

3.2 Uncertainty in Rank Order Filtering

Rank order filters and mathematical morphology share the same requirement regarding a valid ordering relation. Consequently, several criteria used in the ordering construction of nonlinear filters can be used to partially enable the ordering construction in mathematical morphology. Median filter is a rank order filter that is used obtain a pixel within an n-dimensional neighborhood whose value is the closest to the average of the neighborhood.

Spectral Median Filter. Given a filter window W and its corresponding set of image values $\mathfrak{S}_W = \{I(x_0+b), b \in W\}$, each $I(x) \in \mathfrak{S}_W$ is associated with a rank r by an ordering function $h(\cdot)$. In Eq. (10) and (11), the selection of spectrum with rank r is described as finding a spectrum which has $r-1$ number of smaller spectra with regards to a certain $h(v)$. A median filter will then replace the image value or spectrum at the origin $I(x)$ with another value $F(x) = \rho_{W,r}(h(I(x)))$, i.e. an image value that lies within W and has the rank $r = \frac{n_W - 1}{2}$.

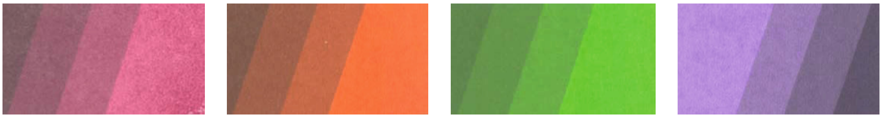
$$\mathfrak{c}_v = \#\{I(x+b) : h(I(x+b)) \leq h(v), \forall b \in W\} \tag{10}$$

$$\rho_{W,r}(h(I(x))) = \bigwedge \{v : v \in \mathfrak{S}_W, \mathfrak{c}_v \leq r\} \tag{11}$$

As the primary requirement of constructing a median filter is an ordering relation, many of the spectral ordering relations provided in Section 2 can be used to construct different spectral median filters. As mentioned before, a lexicographic ordering overestimates the impact of a certain band. Therefore a spectral median filter with a lexicographic ordering O_{lex} which gives priority to shorter wavelengths (Eq. 2) will be compared to an ordering which is based on only the first component of the spectral channels $O_{\lambda 1}$, i.e. the wavelength at 414.62 nm. Other ordering relations to be employed to construct spectral median filters are the ordering based on the sum of energy O_{esum} (Eq. 3), the distance-based ordering with white reflectance spectrum as the reference O_{dw} (Eq. 4), the ordering based on ratio O_{ratio} (Eq. 6), and the conditional ordering based on ratio and angle information $O_{cr\alpha}$ (Eq. 7).

Spectral Median Filters Quality Assessment. Deborah et al. proposed several quality assessment protocols for spectral image processing algorithms [6], where experimental results were provided for the assessment of spectral distance and spectral median filters. In this work, the previously proposed spectral median filters quality assessment protocol is modified so as to be able to evaluate the quality of ordering relations embedded in the filters.

Several pigment patches as shown in Fig. 2 were acquired using a hyperspectral scanner and will be used as the input data to Vector Median Filters and the different spectral median filters that are enabled by the different spectral ordering relations. Vector Median Filter or VMF is a multivariate median filter that is based on aggregate distance. And since VMF was shown to be the most accurate median filter for several classes of random distribution [3], the result of VMF will be used as the benchmark of this quality assessment. All the results of other spectral median filters will be evaluated against this benchmark.



(a) P1 (b) P2 (c) P3 (d) P4

Fig. 2. Four pigment patches acquired by a hyperspectral scanner

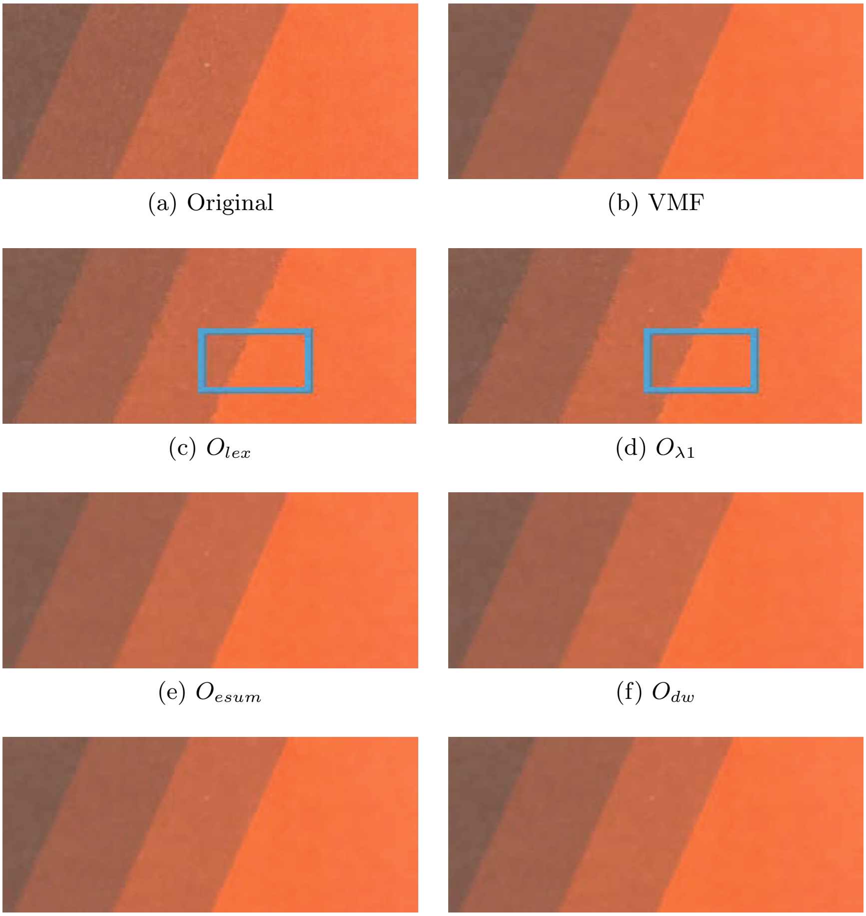
4 Result and Discussion

Table 1 shows image differences between the result of VMF and the 6 spectral median filters. The comparison criteria is pixelwise root mean square error. The results obtained by lexicographic ordering O_{lex} are similar to those obtained by $O_{\lambda 1}$. Such results are as expected, due to the fact that lexicographic ordering is a conditional ordering with the highest priority given to $\lambda 1$. These results explain that the other channels are rarely used in the ordering process and therefore is also explained by the mathematical conjecture in Eq. 8. Hence, there is no significant difference between the results of O_{lex} and $O_{\lambda 1}$. In the case of the pigment patches shown in Fig. 2, better results could indeed be obtained if the lexicographic approach gives more priority to the dominant wavelength of the respective color pigments. Nevertheless, these results for the color pigments illustrate the limitation of lexicographic approach, i.e. when the discriminating spectral channel is unknown and therefore prioritization is given to the wrong channels, the processing result becomes unreliable.

The better performances of O_{esum}, O_{dw}, O_{ratio}, and $O_{cr\alpha}$ compared to those of O_{lex} and $O_{\lambda 1}$ are due to the global approach of the four ordering relations. O_{dw}, O_{ratio}, and $O_{cr\alpha}$ consider the whole dimension of spectra and especially the inner correlation that exists between neighboring spectral channels due to the use of distance function. For O_{esum}, even though it still considers the whole dimension of spectra by reducing a spectrum into a total amount of energy,

Table 1. Average and standard deviation of pixel differences between the results of VMF and other spectral median filters, computed using root mean square error. The more similar performance to that of VMF is considered to be the better ordering relation, hence the smaller values. Significant differences are shown by O_{lex} and $O_{\lambda 1}$, while the other ordering approaches perform similarly.

Ordering relation	P1		P2		P3		P4	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
O_{lex}	8.076	7.009	7.408	10.818	6.963	8.448	7.072	5.033
$O_{\lambda 1}$	7.982	6.890	7.380	10.831	6.929	8.397	7.057	5.049
O_{esum}	4.574	2.980	4.240	2.872	4.317	2.532	4.262	2.864
O_{dw}	4.539	3.131	4.303	2.886	4.305	2.543	4.187	2.832
O_{ratio}	4.596	3.022	4.306	3.088	4.332	2.537	4.297	2.881
$O_{cr\alpha}$	4.596	3.022	4.306	3.088	4.332	2.537	4.297	2.881



(a) Original (b) VMF

(c) O_{lex} (d) $O_{\lambda 1}$

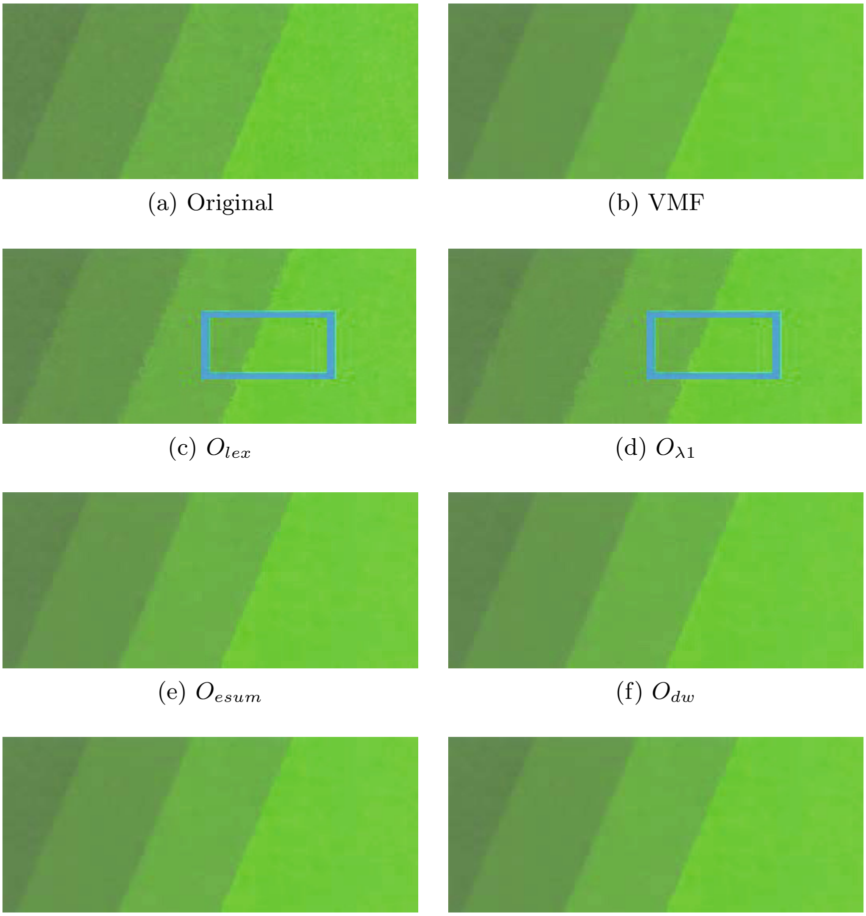
(e) O_{esum} (f) O_{dw}

(g) O_{ratio} (h) $O_{cr\alpha}$

Fig. 3. Results of applying VMF and several spectral median filters with different ordering relations on pigment P2. It can be observed in the regions inside the blue squares that the spectral median filters that are based on ordering relations O_{lex} and $O_{\lambda 1}$ are not able to maintain the edges that exist between two color shades.

it is not considering the inner correlation. In the table the results of O_{ratio} and $O_{cr\alpha}$ are identical. As previously explained for O_{lex} and $O_{\lambda 1}$, $O_{cr\alpha}$ is also a conditional ordering and its second level of condition is almost never used. Again, the mathematical conjecture in Eq. 8 explains this behavior.

While Table 1 only provides the performance of the different spectral median filters globally, Fig. 3 and 4 provides an idea of how the different filters perform locally in the spatial context. One of the desired capabilities of a median filter is to preserve edges from shapes or local gradient and to remove additive noise. In the two figures, original images of pigment P2 and P3 are provided as well



(a) Original (b) VMF

(c) O_{lex} (d) $O_{\lambda 1}$

(e) O_{esum} (f) O_{dw}

(g) O_{ratio} (h) $O_{cr\alpha}$

Fig. 4. Results of applying VMF and several spectral median filters with different ordering relations on pigment P3. Similar to the case of P2 in Fig. 3, the spectral median filters that are based on ordering relations O_{lex} and $O_{\lambda 1}$ are also not able to maintain the edges that exist between two color shades, see regions inside the blue squares.

as the result of the benchmark, i.e. VMF, and the other spectral median filters. In this figure we can observe that O_{lex} and $O_{\lambda 1}$ are not able to retain the edges that exist between two color shades. Finally, if we are to choose between the 6 spectral ordering relations provided in this work, the choice are left with O_{ratio} and $O_{cr\alpha}$, since O_{esum} and O_{dw} do not satisfy total ordering property.

5 Conclusions

This work is a preliminary study on spectral mathematical morphology which explores the possibilities of relating mathematical formalism with the physical nature of a spectrum originating from spectral sensors. Due to the complexity and cost of hyperspectral image acquisition, it is imperative that the following image processing chain is carried out at a metrological level so as to respect the objectives of using such imaging technology. As a consequence, the digital construction of each step in the processing chain must be validated both theoretically and experimentally. Using the notion of distance function allows constructing spectral ordering scheme which respects the constraints induced by hyperspectral image domain. Nevertheless, it yields two questions, i.e. how to select the correct distance function and the correct ordering scheme.

In a previous research [8], several criteria were developed in order to select the most suitable spectral distance function. In this work, we propose several basic ordering relations for spectral data that can respect some expected properties, i.e. total order and idempotency. The first two ordering relations are extended from the classical marginal and lexicographic approaches. Then a relation is proposed and defined from the physical definition of a spectrum, followed by several other ordering relations that are constructed using the total amount of energy and distance function. Among the proposed ordering relations, two that are respecting the required constraints that will satisfy the idempotency property of morphological opening/ closing transforms are proposed, i.e. O_{ratio} and $O_{cr\alpha}$. The quality assessment using median filter shows that the proposed constructions present a reduced level of uncertainty in the ordering.

Several questions must be still improved. The notion of maximum and minimum for spectral data is related to the choice of convergence spectra, hence related to the image processing goals. As the ordering relation is based on reduced ordering using distance functions, all the morphological properties must be enabled at all level as in color domain [13]. The total ordering property of the proposed ordering is respected due to the mathematical conjecture in Eq. 8. While the duality property is satisfied due to the construction of the ordering relation. The next challenge will then be to prove the idempotency for opening and closing operation so as to reach the advanced morphological filters and processing.

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