Clustering of polarization-encoded images

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Polarization-encoded imaging consists of the distributed measurements of polarization parameters for each pixel of an image. We address clustering of multidimensional polarization-encoded images. The spatial coherence of polarization information is considered. Two methods of analysis are proposed: polarization contrast enhancement and a more-sophisticated image-processing algorithm based on a Markovian model. The proposed algorithms are applied and validated with two different Mueller images acquired by a fully polarimetric imaging system. © 2003 Optical Society of America

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1. Introduction

Imaging systems based on measurements of light intensity suffer from several limitations that are inherently related to ignoring the vector nature of light. These restrictions become critical in the following situations: (i) when there is bad illumination, (ii) when transparent objects are present in the imaged scene, and (iii) when strong reflections toward the detector (CCD camera) are caused by metallic edges, among others. Exploiting the polarization of light has been shown to be a useful and powerful technique for overcoming these limitations. There is increasing evidence that imaging the polarization properties of inhomogeneous objects provides a rich set of information about the local nature of the target. Many imaging systems have been designed and built for a wide variety of applications, including medical, metrologic, atmospheric, and remote sensing.

Even though polarization imaging is at the intersection of several disciplines (physics, polarization algebra, and image processing), polarization-encoded images are still considered to provide merely supportive information for other procedures. To our knowledge, except in the paper of Goudail and Réfrégier, the bidimensional structure of polarization images has not been considered extensively. All previously cited references of which we are aware use a physical pixel-based processing approach that does not include the image structure of the measurements.

Polarization imaging includes the parameters of light in the distributed measurements of the polarization. We define Stokes imaging as bidimensional measurement of the Stokes parameters that characterize the polarization state of light imaged by a CCD camera. We also define Mueller imaging as the bidimensional measurement of the Mueller matrices attached to each pixel in the image. Accordingly, polarization-encoded images have a multidimensional structure; i.e. multicomponent information is attached to each pixel in the image.

In this paper we address the analysis of polarization-encoded images and explore the potential for use of this information in classification systems. This study was made possible by a fully polarimetric imaging system that we developed.

2. Background

A. Stokes–Mueller Formalism

The Stokes–Mueller formalism is a widely used method for investigating the interaction of a system with light. Stokes vector (SV) $S$ fully characterizes the time-averaged polarization properties of radiation. It can be defined by the following combinations of complex-valued components $E_x$ and $E_y$ of the electric vector in two mutually orthogonal directions $x$ and $y$ as

$$
S = \begin{pmatrix}
    s_0 \\
    s_1 \\
    s_2 \\
    s_3
\end{pmatrix}
= \begin{pmatrix}
    (E_x E_x^*) + (E_y E_y^*) \\
    (E_x E_y^*) - (E_y E_x^*) \\
    2\Re((E_y^* E_x)) \\
    2\Im((E_x^* E_y))
\end{pmatrix},
$$

(1)
where $s_0$ defines the total intensity, $s_1$ describes the excess of parallel to perpendicularly polarized light, and $s_2$ and $s_3$ convey the nature and handedness, respectively, of the wave.

It is straightforward to show that

$$s_0^2 \geq s_1^2 + s_2^2 + s_3^2,$$

where the equality holds only for completely polarized radiation. When the equality does not hold, the wave is said to be partially polarized. As a consequence of the addition theorem of incoherent beams, any SV can be decomposed as

$$S = S_u + S_p$$

$$= \begin{bmatrix} s_0 - (s_1^2 - s_2^2 + s_3^2)^{1/2} \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} s_1 \\ s_2 \\ s_3 \end{bmatrix},$$

where $S_u$ and $S_p$ are the SVs of the unpolarized and the completely polarized components, respectively, of the radiation. An interesting method of depicting the polarization state involves the use of a Poincaré sphere for which a polarization state is marked as a point within this sphere. This concept is extremely powerful and provides a handy way to illustrate polarization states graphically.

A Mueller matrix relates the Stokes vector of the incoming waves linearly to the Stokes vector of the outgoing ones. It characterizes the transfer of energetic and polarizing properties of the system to the beam. Formally, this can be written as

$$S_o = MS_i,$$

where $M$ is the system’s Mueller matrix, $S_o$ is the outcome SV, and $S_i$ is the incoming SV.

Our main interest in the Stokes–Mueller formalism lies in that fact that all quantities involved in definitions are quadratic (intensities) and therefore are accessible from measurements with quadratic detectors (photodiodes) and CCD cameras.

### B. Physical Considerations

If the system is passive it should not overpolarize, and the energy of the emerging wave should not exceed the energy of the incident wave. These conditions impose constraints on the elements of the corresponding Mueller matrix. A Mueller matrix is then said to be physically attainable if, and only if, it satisfies these constraints.

Inasmuch as practical Mueller matrices are obtained indirectly as results of combined experimental and algorithmic procedures, it is important to define testing procedures clearly. The issue has been addressed by several authors, among whom Xing10 has investigated the peculiar case of Howell’s collimator–radiometer10 and has questioned the validity of the Stokes–Mueller calculus in such a case. The trace condition of Fry and Kattawar11 was used by Kostin-
It can be shown that the measured intensity at the location of pixel $I_{ij}$ is a function of the angular positions of quarter-wave plates $\alpha_1$ and $\alpha_2$. For fixed angle positions of the two quarter-wave plates, $\alpha_1^k$ and $\alpha_2^l$, this intensity can be written as:

$$I_{ij} = \frac{1}{2} (1 - \cos^2 2\alpha_2^k - 0.5 \sin^2 4\alpha_2^k) \times \sin 2\alpha_2^k \mathbf{M}_j \begin{bmatrix} 1 \\ \cos^2 2\alpha_1^l \\ 0.5 \sin^2 4\alpha_1^l \\ \sin 2\alpha_1^l \end{bmatrix},$$

(5)

where $\mathbf{M}_j$ is the pixel's $(i,j)$ 4 $\times$ 4 Mueller matrix.

To fully determine $\mathbf{M}_j$, requires 16 intensity measurements that correspond to four positions of both angles $\alpha_1^k$ and $\alpha_2^l \; (k, l = 1, 4)$, yielding

$$\mathbf{M}_j = \mathbf{A}^{-1} \mathbf{I}_j \mathbf{P}^{-1},$$

(6)

where

$$\mathbf{A} = \begin{bmatrix} 1 & -\cos^2 2\alpha_2^1 & -0.5 \sin^2 4\alpha_2^1 & \sin 2\alpha_2^1 \\ -\cos^2 2\alpha_2^2 & 1 & -0.5 \sin^2 4\alpha_2^2 & \sin 2\alpha_2^2 \\ -\cos^2 2\alpha_2^3 & -0.5 \sin^2 4\alpha_2^3 & 1 & \sin 2\alpha_2^3 \\ -\cos^2 2\alpha_4^4 & -0.5 \sin^2 4\alpha_4^4 & -\cos^2 2\alpha_4^4 & 1 \end{bmatrix},$$

(7)

$$\mathbf{P} = \begin{bmatrix} 1 \\ \cos^2 2\alpha_1^1 \\ 0.5 \sin^2 4\alpha_1^1 \\ \sin 2\alpha_1^1 \\ \cos^2 2\alpha_1^2 \\ 0.5 \sin^2 4\alpha_1^2 \\ \sin 2\alpha_1^2 \\ \cos^2 2\alpha_1^3 \\ 0.5 \sin^2 4\alpha_1^3 \\ \sin 2\alpha_1^3 \\ \cos^2 2\alpha_1^4 \\ 0.5 \sin^2 4\alpha_1^4 \\ \sin 2\alpha_1^4 \end{bmatrix}. $$

(8)

Adequate values of $\alpha_1^k$ and $\alpha_2^l \; (k, l = 1, 4)$ that maximize determinants $\mathbf{A}$ and $\mathbf{P}$ are obtained by minimization to avoid matrix singularities.

Much attention has been paid to calibration to provide Mueller images: The maximum relative error over the whole image is $\sim 0.1$% for the free-space Mueller matrix and less than 1% for the Fresnel reflection matrix of a BK7 prism’s surface.

An interferential filter (10-nm bandwidth) is used in front of the camera to permit observation at various wavelengths while the incoherent source is used.

Sixteen intensity images provide a linear system, which can be inverted to yield a Mueller image of the object for which a Mueller matrix is attached to each pixel. The Mueller matrix image contains all the local relevant polarization information about the object. The main problem is to link these matrices to physical interaction mechanisms related to object features that are relevant to a specific application. For instance, the imaging polarimeter works as a full polarimeter; i.e., both the polarizer and the analyzer are required for the measurements.

3. Polarization-Based Clustering

A. Description of Objects

In this study, two objects were used: a plant leaf and a manufactured object. The manufactured object consists of two shapes made from two different transparent thin films (cellophane for wrapping food). The shapes were sandwiched between two glass plates. A black-painted sheet was inserted in the back of the assembly to produce an adequate signal level when an incoherent source was used. For the Markovian segmentation task discussed below, the black sheet was removed because the algorithm shows how to handle a low signal level effectively. The whole assembly was mounted upon a metallic base.

The plant leaf was imaged under backlight illumination, whereas for the constructed object the measurements were made with an incidence angle of 20°. Mueller images were acquired from the intensity measurements. For this application a 640 $\times$ 512 pixel resolution was used with an image definition of 12 bits.

Figures 2 and 3 show the Mueller images for the two objects. The first Mueller element image (upper left corner, Figs. 2 and 3) corresponds to a conventional intensity image ($m_{00}$ Mueller element image).

B. Analysis

The reason for using a clustering process is to classify the pixels of an image into different sets, each set corresponding to an object in the imaged scene. Segmentation can prove a difficult task when the objects are transparent. If in addition the images have low contrast and many bright spots, segmentation based only on intensity features is almost impossible. Hence we investigate clustering algorithms based on a polarization analysis of the scene.

If we consider all the information contained in the various dimensions of a Mueller image, a cluster is no longer characterized by a single value. A cluster can now be described by different physical attributes.

Figure 4 shows possible ways to analyze Mueller images. After image acquisition and physical validity tests, two techniques are considered for analysis. In the first, classic multichannel clustering algorithms are coupled with possible a priori treatment on the physical basis applied to Mueller images. The second method addresses the use of more sophisticated algorithms that can account for specifics of the polarization images.

A polarimetric image contains many data (16 val-
ues per pixel for a full polarimetric image) and cannot be exhibited in the form of standard images. This approach provides workable images that can be simple to grasp and for which classic image-processing techniques can be used.

Among the techniques that deal with such multidimensional problems to minimize a formal function, one of the most widely used and studied is $K$-means clustering. This technique is an unsupervised classification algorithm for which clusters are found in a way similar to that of the previously introduced iso-data algorithm.

Mueller channels are not the optimal set of images to be input to the $K$-means algorithm. Indeed, no workable result was obtained with our images. Thus it is reasonable to search for a suitable polarization contrast-enhancement procedure that uses all the polarimetric information and reduces the dimensionality of the multicomponent image.

Parameterization of the Mueller matrix found elsewhere in the literature, such Lu–Chipman polar decomposition and Cloude’s decomposition based on the coherency matrix, provides sets of candidate images for clustering. For our example, the polar decomposition technique performs better than Cloude’s model. Figure 5 shows the manufactured object segmented by polar decomposition. The two shapes are well separated from the background, but the method does not separate the two shapes into two different classes. The polar decomposition fails to segment the leaf object properly, however.

C. Clustering by Polarimetric Contrast Enhancement

The methods of polarimetric contrast enhancement remain pixel based, and spatial polarization information is not considered. A possible solution is to exploit the availability of Mueller images to enhance the polarimetric contrast in the outgoing Stokes image while the input illumination state spans the entire Poincaré sphere. The whole procedure is explained in the following algorithm:

1. Choose an input state on the Poincaré sphere.
2. Calculate the resultant Stokes image.
3. Find ellipticity $I(e)$, orientation $I(\theta)$, and polarization degree images $I(P)$.
4. Cluster multidimensional image $I(\varepsilon, \theta, P)$ to $K$ classes $C_i$, defined by their centers $v_i$.

5. Calculate distance $d = \sum_{i,j=1,k} d(v_i, v_j)$, where $d(v_i, v_j)$ is the distance between $v_i$ and $v_j$.

6. Use the simplex algorithm to find the next input state such as to maximize $d$; return to step 2.

When we compare Figs. 6 and 7 with the intensity images (m00 Mueller element image in Figs. 2 and 3), we conclude that the algorithm greatly enhances the objects’ images that we have to segment. At least for our examples, this algorithm provides better results than those obtained by polar decomposition of the Mueller image for the manufactured object and for the plant leaf, where the latter fails to produce a workable image. This illustrates the usefulness of exploiting the polarization information under conditions of bad illumination. The algorithm is interesting, as it quickly converges and can be implemented easily for a real-time imaging polarimeter.

In Section 4 we present the main features of the Markovian segmentation algorithm that uses a Mueller image cube.

4. Image Segmentation

Image segmentation remains a difficult issue, particularly when what is unsupervised. As the state of instrumentation evolves to produce increasingly finer resolution in spectral, spatial, and temporal data, increasingly more sophisticated techniques are required for handling these data properly. Statistical approaches have proved successful as robust methods of analysis and segmentation. A Bayesian scheme based on a Markov model is attractive when one is dealing with large amounts of data.
In the context of multimodal polarimetric images, we propose to adopt a Markovian model that exhibits a good ability to learn the required model parameters in an efficient and fast manner.

A. Multi-Image Segmentation

The segmentation task consists in estimating the underlying unobserved quantity \( X = x \) from the observed quantity \( Y = y \), where \( y = (y_s)_{s \in S} \) is the multi-image observation field to be segmented; \( Y \) is therefore a field of vector on grid \( S \), where each vector \( y_s \) corresponds to the vector of quantized information observed on each image of the data cube. In multispectral imagery, \( y_s \) are the observed luminances for a number of broad wavelength bands; in hyperspectral imagery, \( y_s \) code the measure of hundreds of narrow contiguous-wavelength bands at the same spatial position \( s \); in medical applications with multimodal sensors, voxel \( y_s \) stands for given different modality data (magnetic resonance imaging, TEP, scanners, etc.) at one location \( s \) in the data cube. In the context of remote polarimetric imagery, \( y_s \) can be the Stokes vector [Stokes imaging, \( \dim(y_s) = 4 \)]: In active polarimetric imagery, \( y_s \) is described by the Mueller matrix [Mueller imaging, \( \dim(y_s) = 16 \)]: In all cases the amount of data to be considered is large, requiring new segmentation techniques. In the Markovian context of unsupervised Bayesian segmentation, \( y \) stands for the observed images and \( X \) represents the segmentation map that we have to recover. To do that we need to estimate all the parameters that define joint distribution \( P(X, Y) \), i.e., \( P(X) \), the distribution of \( X \), and \( P(Y/X) \), the distribu-

Fig. 4. Steps in the three algorithms for clustering Mueller images. The Markov-model-based algorithm directly processes 16 Mueller channels (steps a–b). The polar decomposition algorithm is mainly a physical processing of polarization data (steps c–e). The polarization-contrast enhancement algorithm uses polarization-based information to reduce the data's dimensionality and to provide a more suitable image for classic image-processing algorithms.

Fig. 5. Retardance parameter image obtained by polar decomposition. The two shapes are well separated from the background, but the method does not separate the two shapes into two different classes.

Fig. 6. Result of polarization-contrast enhancement of the manufactured object. This result is to be compared with the \( m_{00} \) Mueller element image (Fig. 2) and with Fig. 5.

Fig. 7. Result of polarization-contrast enhancement of the plant leaf. This result is to be compared with the \( m_{00} \) Mueller element image (Fig. 3). Polar decomposition fails to give a good result for this object.
tion of \( Y \) conditional on \( X \). Markovian segmentation algorithms used to obtain segmented map \( X \) from observed image \( Y \) are generally decomposed into three main phases:

1. **Initialization.** The objective is to provide a first estimation \( \Phi \) of the data-driven parameters that link the intensity and the label on each site \( s \). Clustering algorithms (e.g., the C-means algorithm) can be used in an efficient way. For the model parameter, corresponding to Markovian properties of label field \( X \), the \( \Phi \) values are generally fixed according to their initial a priori meaning.

2. **Parameter estimation.** This estimation is achieved by use of estimation algorithms (EM, SEM, etc.). For example, the ICE approach\(^{34} \) is based on an iterative estimation of the conditional expectation \( \Phi = \{ \Phi_s, \Phi_y \} \) according to the relation:
\[
E_{\Phi_n}[X_{n+1} | \Phi_n, X_n, Y] = \frac{E_{\Phi_n}[X_{n+1} | X_n, Y]}{P(\Phi_n, X_n, Y)}
\]
where \( X_n \) is a manifestation of \( X \) drawn with an a posteriori density function.

3. **Segmentation.** The labeling process is then achieved by use of a Bayesain-criterion-based segmentation rule (maximum a posteriori probability, mode of posterior marginals, mean field, . . .).

The parameter estimation phase and the segmentation process are successively iterated until a convergence criterion is reached.

A twofold difficulty must be overcome: The a posteriori density has to be estimated if possible in an exact, efficient, and fast manner, whereas the parameter estimation has to be robust to multidimensional strong noise. In our case, we consider the class of generalized Gaussian laws\(^{35} \) that enables a variety of observation processes to be accommodated within the same framework. The segmentation method is based on a Markov model in scale on a quad tree.\(^{36} \) A quad-tree-based approach offers the well-known advantages of standard hierarchical techniques (improved robustness, ability to deal with multiresolution data) while it allows for noniterative inference as in the case of hidden Markov chains.\(^{37} \)

**B. Motivations for Using Bayesian Inference and a Hierarchical Markovian Model**

We have developed an original segmentation scheme consisting of two main steps. In practice, the first step is important to provide correct initialization of the label map: We adopt a maximum-likelihood criterion (i.e., a parameter estimation of a mixture of probability-density functions and a log-likelihood computation) to provide the initial label map. This step is unsupervised, apart from the number of classes \( K \), which is a given in our case. The first step is based only on the observation vector for each of the pixels, without any spatial constraint between a pixel and its neighborhood taken into account. If the images contain little noise, this step sometimes is sufficient for some applications. In our case, strong speckle noise and weak contrast ensure that luminance and neighborhood labels be considered when each pixel is labeled.

As a consequence, we propose using a hierarchical hidden Markov model (HHMM) that takes into account both the multimodal observations and a spatial regularization constraint. This regularization constraint is modeled in scale on a quad-tree structure. The usefulness of HHMMs stems from their ability to estimate the HHMM parameters and to provide a form of context handling for image segmentation.\(^{36} \) An iterative update algorithm re-estimates the parameters of a given hidden Markov model to produce a new model that has a higher probability of generating the given observations. This re-estimation is continued until no more significant improvement in probability can be obtained, after which convergence toward the local minimum is found. The method of hierarchical image analysis is an elegant computational construct that allows us to take advantage of a coarse-to-fine strategy, to refine the statistical analysis, which is then greatly simplified. In particular, HHMM on a quad tree can lead to mode of posterior marginals segmentation, as the posterior distribution on each site of the image is explicitly and exactly obtained, without Monte Carlo sampling as needed for a Markov random field.\(^{38} \) This property of quick convergence time added to the low computational complexity of the algorithm makes our method attractive for multimodal polarimetric image segmentation.

Let \( G \) be a graph composed of a set of nodes \( S \). A tree is a connected graph with no cycle, for which, as a consequence, each node apart from root \( r \) has a unique predecessor, its parent, on the path to the root. A quad tree, as illustrated in Fig. 7, is a special case of tree for which each node, apart from the terminal nodes, the leaves, has four child nodes. The set of nodes \( S \) can be partitioned into scales \( S = S^0 \cup S^1 \ldots \cup S^R \), according to the path length of each node to the root. Thus \( S^R = \{ r \} \), \( S^n \) involves \( 4^R-n \) sites, and \( S^0 \) is the finest scale formed by the leaves. We consider a labeling process \( x \), which assigns a class label \( x_s \) to each node of \( G \):

\[
x = \{ x^n_s \}_{s \in S^n}, \quad x^n = \{ x_s, \ s \in S^n \},
\]

where \( x_s \) takes its values in the set \( \Delta = \{ \omega_1, \ldots, \omega_K \} \), of the \( K \) classes or segments.

A number of conditional independence properties are assumed. First, \( x \) is assumed to be Markovian in scale; i.e.,

\[
P(x^n | x^k, k > n) = P(x^n | x^{n+1}).
\]

To simplify the notation we denote the discrete probability \( P(X = x) \) by \( P(x) \). It is also assumed that the probabilities of interscale transitions can be factorized in the following way\(^{36} \):

\[
P(x^n | x^{n+1}) = \prod_{s \in S^n} P(x_s | x^-_s),
\]

where \( x^-_s \) designates the single father of a site \( s \), as illustrated in Fig. 7.

Finally, the likelihood of observations \( y \) condi-
tioned on \( x \) is expressed as the following product (assuming conditional independence):

\[
P(y|x) = \prod_{n=0}^{R} P(y^n|x^n) = \prod_{n=0}^{R} \prod_{s \in S^n} P(y_s|x_s), \tag{12}
\]

where \( \forall s \in S^n, \forall n \in [0, \ldots, R], P(y_s|x_s = \omega_i) = P_i^n(y_s) \) captures the likelihood of the data \( y_s \) formed by the vector of the Mueller matrix elements, at site or pixel \( s \) of scale \( n \), given label \( \omega_i \).

We obtain a labeling of each pixel at each level of the quad tree, even if observations lie only on the finest level. Indeed, the two-step computation of posterior marginals propagates available information all over the tree. The bottom-up step spreads the influence of data to other levels up to the root. Then the top-down step computes the posterior marginals, with this information taken into account.

If observations are available for other nodes of the tree, this algorithm merges all the observations to produce a more accurate segmentation result. The root of the quad tree is also a node of the pyramid.

In this paper, data are available only at the finest level \( (n = 0) \), under a vector shape. When no observation exists \( (n > 0) \) or when the site at scale 0 does not belong to an area that is considered classifiable (e.g., a known erroneous pixel or missing observation), likelihood \( P_i^n(y_s) \) is set to 1.

From these assumptions it can easily be inferred that joint distribution \( P(x, y) \) follows a Gibbs law, the expression of which is given by

\[
P(x, y) = \prod_{s \in r} P(y_s|x_s) \prod_{s \in S} P(y_s|x_s). \tag{13}
\]

One interesting characteristic of this model lies in the possibility of computing exactly the posterior marginals \( P(x_s) \) and \( P(x_s, x_{s'}|y) \) at each node \( s \) with two passes. These computed expressions will be used first in the iterative parameter estimation step, as described in Fig. 8. The segmentation label map \( \hat{x} \) to be determined is finally given by

\[
\hat{x}_s = \arg \max_{\omega_i \in \Delta} P(x_s = \omega_i|Y = y). \tag{14}
\]

This approach on a quad-tree structure exhibits similarities to the Baum–Welch algorithm used for hidden Markov chains. This is an iterative update

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**Fig. 8.** Graph of dependency that corresponds to a quad-tree structure. Filled circles, labels; open circles, observations. The segmentation algorithm re-estimates iteratively the parameters of a given hidden in-scale Markov model to produce a new model that has a higher probability of generating the given observation sequence. This re-estimation procedure is continued until no more significant improvement in parameters can be obtained. The two-step computation of posterior marginals propagates available information all over the tree: on one hand, the bottom-up step spreads the influence of data to other levels up to the root; on the other hand, the top-down step.

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**Fig. 9.** Schematic illustration of the Markovian segmentation process used in this study.
Starting from an initial label map given by a maximum-likelihood-based algorithm whose parameters are estimated by a C-means algorithm, this technique converges to the maximum of the \textit{a posteriori} probability-density function that is highly multimodal; therefore a good initialization is needed to guarantee the fast convergence of the procedure to the global optimum.

This approach is robust and accurate, as shown by the label map obtained on Mueller images (Figs. 9 and 10). Two conclusions can be drawn from this analysis: First, a hierarchical Markovian assumption is able \textit{per se} to provide a homogeneous segmentation map in the presence of strong noise; second, the usefulness of in-scale Markovian models stems from the ease with which its parameters can be learned through the ICE reestimation procedure on the quad tree (the bottom-up step spreads the influence of data to other levels up to the root; then the top-down step computes the posterior marginals, taking this information into account and from its ability to provide a form of context handling in pattern recognition.

5. Conclusions and Future Research

Polarimetric imagery can be used effectively to characterize objects even under conditions of low radiance. It is particularly useful in determining the shape and composition of targets. In this study we have investigated the usefulness of coupling polarization information with image-processing techniques as opposed to the pixel-based treatment usually used. Considering the bidimensional consistency of polarization information is shown to be very efficient. Indeed, good results were obtained by use of a simple and fast polarization-contrast enhancement algorithm. However, only the HHMM was able to segment the manufactured object accurately at a low signal level (no black-painted sheet was present). Some artifacts (block effects) remain as a result of the quad-tree structure. Because the first results produced convincing label maps, and order to avoid such phenomena on a skeletonized structure (Fig. 10), we intend to investigate the use of another Markovian model based on hidden chains. Another idea that we intend to develop consists in using principal-component analysis on Mueller channels before segmenting to enhance the effectiveness of segmentation.

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