CLASSIFICATION OF A REFERENCE IMAGE USING AUXILIARY IMAGES

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1. INTRODUCTION

In the classical multidimensional image Bayesian classification the images set must all have the same group of classes. This boundary condition can be very restrictive when considering a multi source classification process, where some class could not be represented in one or more images. This work presents a new classification approach in which the images can have different group of classes. These different classes can be related to the sensor characteristics, which can detect different aspects of the same scene. It is shown a variant of the multidimensional image Bayesian classification approach, named Generalized Bayesian Approach (GBA), in which a reference image is chose and the information in the other images, with different classes, can be used in the classification task. In an experiment with SAR simulated images, the GBA achieved better performance than the Cascade Classifier.

2. GENERALIZED BAYESIAN APPROACH

If we consider a set with N independent images and each of then with the same M classes, the minimum Bayes Risk can be reached by the Global Membership Function (GMF) [1] using the decision rule state as:

$$\breve{x} \mapsto w_m \Leftrightarrow P(w_m)\prod_{n=1}^{M} p_X(x^{(n)} \mid w_m) = \max_k P(w_k)\prod_{n=1}^{M} p_X(x^{(n)} \mid w_k) \quad (1)$$

where $\breve{x} = (x^{(1)}, x^{(2)}, ..., x^{(N)})$ is the observation, w_m with m = 1, 2, …, M is the class, $P(w_m)$ is the *a priori* probability of w_m and $p_X(x^{(n)} \mid w_m)$ is the conditional probability of $x^{(n)}$ given that the w_m class is through. Such classifier is named “Cascade Classifier” [2].

We now consider that each image in a set of N images has their own classes represented by $w_{m_n}^{(n)}$ with n = 1, 2, …, N and m_n = 1, 2, …, M_n where M_n is the number of classes in image n. For this case if we choose the observation one ($x^{(1)}$) as a reference image the Bayes Risk is minimized by the decision rule given by:

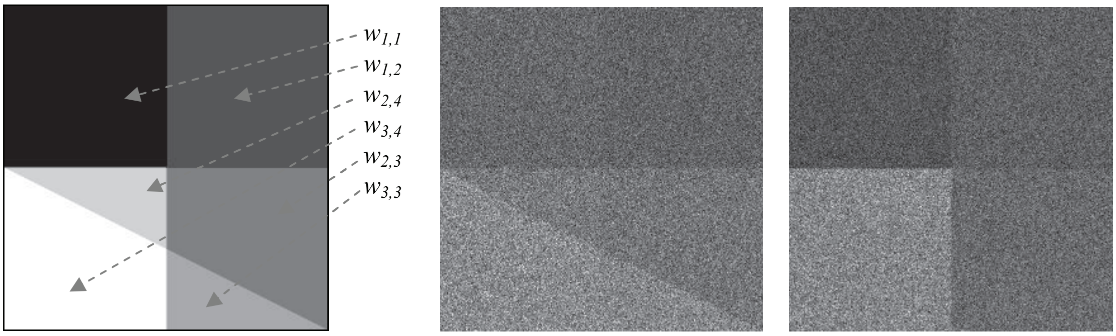
$$x^{(1)} \mapsto w_{m_1}^{(1)} \Leftrightarrow F_{m_1}(\breve{x}) = \max_{m_a} F_{m_a}(\breve{x}) \quad (2)$$

where the discriminated function $F_{m_a}(\breve{x})$, using GBA, is state as

$$\begin{aligned} F_{m_1}(\breve{x}) = p_X(\breve{x}, w_{m_1}^{(1)}) &= \sum_{m_2=1}^{M_2} \sum_{m_3=1}^{M_3} ... \sum_{m_N=1}^{M_N} p_X(\breve{x}, w_{m_1}^{(1)}, w_{m_2}^{(2)}, ... w_{m_N}^{(N)}) \\ &\overset{\text{Chain Rule}}{=} P(w_{m_1}^{(1)}) \sum_{m_2=1}^{M_1} \sum_{m_3=1}^{M_2} ... \sum_{m_N=1}^{M_N} p_X(\breve{x} \mid w_{m_1}^{(1)}, w_{m_2}^{(2)}, ... w_{m_N}^{(N)}) \prod_{n=2}^{N} P(w_{m_n}^{(n)} \mid w_{m_1}^{(1)}, w_{m_2}^{(2)}, ... w_{m_{n-1}}^{(n-1)}) \end{aligned} \quad (3)$$

3. EXPERIMENT DESCRIPTION AND DISCUSSION

In order to evaluate the performance of the GBA, a classification experiment was conducted using simulated images. Fig. 1 shows a simulated scene with 6 classes (ground truth) that are observed by two different sensors which products two different and independent images. It was simulated four sets of images as One-Look SAR images (Rayleigh distributed) according to the distributed classes presented in Fig. 1(a) and the characteristics in Table 1. In Fig. 1(b) and 1(c) it is shown the Set 1.



(a) (b) (c)

Fig. 1: Classes definition. a) Six classes as ground truth, b) Three predominant classes in the first image (reference image) and c) Four predominant classes in the second image (auxiliary image).

Table 1: Images parameters

		Mean values of he Rayleight r.v. for the classes					
Classes:		$w_{1,1}$	$w_{1,2}$	$w_{2,3}$	$w_{2,4}$	$w_{3,3}$	$w_{3,4}$
Set 1	Image 1	20+0.6	20-0.6	25-0.6	25+0.6	30-0.6	30+0.6
	Image 2	30	35	40-0.6	45+0.6	40+0.6	45-0.6
Set 2	Image 1	20+0.6	20-0.6	25-0.6	25+0.6	30-0.6	30+0.6
	Image 2	30	45	60-1	75+1	60+1	75-1
Set 3	Image 1	20+1	20-1	35-1	35+1	50-1	50+1
	Image 2	30	35	40-0.6	45+0.6	40+0.6	45-0.6
Set 4	Image 1	20+1	20-1	35-1	35+1	50-1	50+1
	Image 2	30	45	60-1	75+1	60+1	75-1

The images were filtered by a 5x5 mean filter and are then classified according to the decision rules (1) and (2). Table 2 shows the classification accuracy given by the Kappa coefficient.

Table 2: Kappa values for the classification.

Classification Scheme	Decision Rule	Set 1	Set 2	Set 3	Set 4
a) Image 1 classification in 3 classes	(1)	0.59±0.02	0.59±0.02	0.94±0.01	0.94±0.01
b) Image 1 classification in 6 classes	(1)	0.26±0.01	0.26±0.01	0.43±0.01	0.43±0.01
c) Image 1 and 2 classification in 6 classes	(1)	0.55±0.01	0.73±0.01	0.78±0.01	0.91±0.01
d) Reference Image 1 classification in 3 classes	(2)	0.74±0.02	0.78±0.010	0.94±0.01	0.96±0.01

The results in Table 2 show the decision rule (2) achieved a better performance than decision rule (1), considering all the classification schemes. The images Set 1 result is significant because it was the most critical due the small differences between the classes in the reference images. Table 2 shows that the use of GBA out performer the Cascade Classified in 0.48 for the classification scheme (b) and 0.15 for the classification scheme (a).

4. REFERENCES

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