Using Color for Fish Species Classification

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***Abstract*—This paper presents an application dedicated to mobile devices whose objective is to classify fish species, using images and concepts of Computer Vision and Artificial Intelligence. The application was developed to Android smartphones with the help of OpenCV Computer Vision library for classification and training phases. The techniques employed in the description of the images are based on Bag of Visual Words applied to color images. They are: HSV and RGB color histograms, Bag of Visual Words, Bag of Features and Colors, Bag of Colors and Bag of Colored Words (BoCW). For the species classification, three types of classifiers was used: Support Vector Machine (SVM), Decision Tree and K-Nearest Neighbors algorithm (KNN). In the experiments several parameters for all the classifiers were tested in order to find the best results for classification. To compare the performance of the feature extraction techniques, as well as the classifiers, the metrics F-Score were used as the main metric and the Area Under the Curve (AUC) as an auxiliary metric. The technique with best result was BoC using the SVM classifier.**

I. Introduction

A new world class aquarium is being built in the state of Mato Grosso do Sul, Brazil, and the results presented in this paper are part of a project that aims at building mobile applications to be used by the visitors of this aquarium, as part of the assistance provided to the tourism industry and branch companies. In particular, applications that can automatically recognize different species and bring information about these species to the visitors mobiles are being developed.

Fig. 1. Pantanal Aquarium, Campo Grande, state of Mato Grosso do Sul, Brazil.

The identification of fish species is not easy, even for humans. Nery et al. [1] reported that fishes have, at least, 47 differing characteristics that can be used in this process. Using a Bayesian classifier and attribute vectors encoding these 47 characteristics, they reached an accuracy rate around 90% for a identification task involving 6 different fish species. Rova et al. [2] and Huang et al. [3] also reported accuracy rates around 90%, but in experiments using 2 and 10 species, respectively. Rova used support vector machines on texture and shape attributes and Huang proposed a hierarchical classifier working on 66 different attributes based on color, shape and texture.

Rodrigues [4] combined Principal Component Analysis [5] with SIFT features to encode shape, appearance and movement styles of species. As for machine learning, they experimented with algorithms based on artificial immune systems, reaching an accuracy of 92% with 9 species of fish. The highest accuracy reported among the reviewed papers was 97.4%, from the work of Alsmadi et al. [6] with 7 species. They used geometrical parameters and neural networks to select the most discriminative extractors and decision trees for supervised learning.

Iscimen et al. [7] used centroid-contour distance method in order to classify fish species with two dorsal fins. These distances were used as features and Nearest Neighbour algorithm was used for classification. In this situation, 15 species were classified with 95% general accuracy achievement.

Analyzing 6 species of fish, Hu et al. [8] scores an average of 97.96 of accuracy using support vector machine. The images analyzed were obtained through mobile devices in a fish farm in China, and subsequently, texture and color informations were extracted from the images by a workstation.

In our work, a dataset comprising images from 28 different fish species has been used to test five extractors and three supervised learning strategies. In order to measure the effect of colors in this task, we have compared the Bag of Visual Words algorithm (BoVW), with strategies that extend BoVW to incorporate chromatic information and global color histograms in the HSV and RGB color spaces. The two strategies based on BoVW that have been tested were the Bag of Features and

Colors (BoFC) [9] and the Bag of Colors (BoC) [10]. Was also used a technique that uses BoW with the color information provided by HSV color histogram called in this paper Bag of Colored Words (BoCW). A brief review of these techniques will be presented in the following sections.

Three standard supervised learning techniques have been coupled with each of these features extractors in order to produce 15 different species recognizers. The learning techniques, which are widely used in similar computer vision problems, are the J4.8 decision tree classifier [11], the k-nearest neighbors (KNN) [12] and the optimized support vector machine proposed by Platt [13].

Several experiments have been conducted in order to optimize the many parameters and to compare the techniques. The dataset has 40 segmented images from fishes of each of the species and have been collected using common cameras available in mobile phones during visits to some small aquariums and ornamental fish stores in Brazil. Using the macro averaged F-Score as the main comparison metric, we were able to identify that SVM coupled with BoC or the 3D color histograms presented the best results, with a maximum F-Score of 94.1%, outperforming the results of Huang et al. [3], the only work reviewed which used as many different species as ours.

The next section reviews the feature extractors used in our experiments. The image dataset is described in Section III, followed by a brief presentation of the comparison metrics used. The experimental setup, results and discussion are presented in section IV and V respectively. The last sections are reserved for conclusions.

II. Feature Extractors

In this section the five feature extractors used in our experiments are described. Before presenting the extractors, the SURF [14] algorithm, used in two of these five extractors, is reviewed.

A. Speeded Up Robust Features (SURF)

Speeded Up Robust Features (SURF) is an algorithm to detect and describe local features in images. It is one of the many available local descriptors that can be used with Bag of Visual Words based global feature extractors, like for instance, SIFT and Harris corner detector. The key points found by SURF, along with techniques such as BOW, can be used to describe and compare images making it a technique widely used in computer vision. SURF has been chosen due to its reported lower computational cost and is composed of the two main modules described next: key point detection and key point description.

1) Keypoint Detection: A keypoint is the central pixel of a small image region with a high gradient in one or several directions. SURF uses an approximation of the Hessian matrix in multiple scales and non-maximum suppression in order to detect keypoints. Integral images are used to speed up several calculations. Besides the pixel coordinates and scale, each keypoint is associated to the main direction of its approximated gradient. Figure 2 illustrates the key points detected by SURF in two images. The size and direction of the yellow lines are respectively related to the scale and gradient direction of the keypoint. Blue and red colors are used to indicate changes from darker to lighter regions (blue) or the reverse (red).

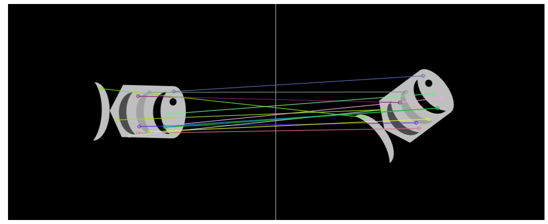


Fig. 2. Set of keypoints detected by SURF in a fish image. Note that is possible to compare both of images comparing these keypoints.

2) Keypoint Description: For each keypoint detected, a 64 descriptor vector is constructed using the responses of a Haar wavelet calculated on several subregions around the keypoint and aligned with the main orientation of the keypoint in order to achieve some invariance to image rotations.

B. Bag of Visual Words

Given the keypoints and descriptors extracted using SURF, or another local feature extractor, the BoVW generates a fixed sized vector the can be used as a global descriptor for an image and feed a feature vector based machine learning algorithm.

BoVW can be described in four steps, as shown in Figure 3. The first step detects and describes all keypoints for all the training images (Figure 3 (a)). Given the descriptor vectors for all these keypoints, a clustering algorithm, such as k-means, is performed to partition the set of keypoints into k clusters (Figure 3 (b)). Each of these k cluster is called a visual word and k, which is a parameter calculate experimentally, is the dictionary size. To describe a new image, the keypoints are extracted and assigned to one of the k clusters (Figure 3 (c)) using some similarity measure between descriptor vectors. In this way, each keypoint is associated with a visual word. Finally, a histogram of size k that counts the frequency of each visual word occurring in the image is built (Figure 3 (d)).

The next two techniques, inspired on the Bag of Visual Words, insert color information in the image descriptor.

C. Bag of Features and Colors

The Bag of Features and Colors (BoFC) [9] extends BoVW by adding color information to each keypoint descriptor vector before the clustering step. BoFC calculates the average (Equation 1) and the standard deviation (Equation 2) for the R, G and B channel of the RGB color space in a 5×5 pixels area surrounding the keypoint.

$$\overline{E_i} = \frac{1}{N}\sum_{j=1}^{N} P_{ij} \tag{1}$$

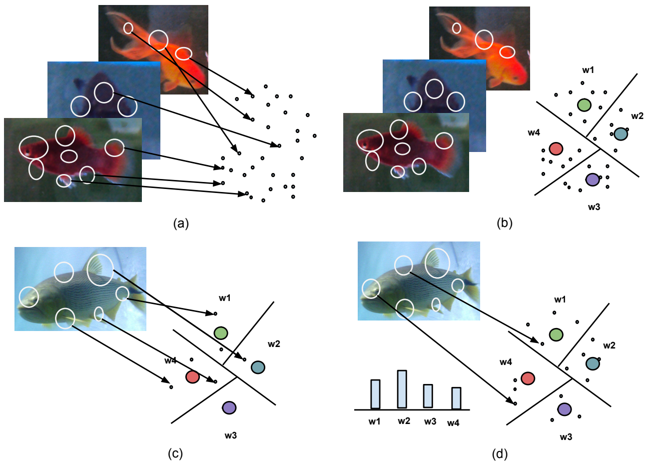


Fig. 3. Graphical representation of the BoVW algorithm. Figure 3 (a) illustrates the keypoints extracted from all training images. Figure 3 (b) shows four clusters found by the k-means to compose the visual dictionary. Figure 3 (c) illustrates the assignment of the keypoints to the clusters of an image and finally, Figure 3 (d) shows the histogram that counts the occurrence of each cluster.

$$\alpha_i = \left[\frac{1}{N} \sum_{j=1}^{N} (P_{ij} - \overline{E_i})^2 \right]^{1/2} \quad (2)$$

In Equation 1 and 2, i represents the i-th color channel, j represents the j-th pixel of the image, P_{ij} is the value of pixel j for the i-th color channel and N is the number of pixels, in this case, $N = 25\,(5 \times 5)$. The final descriptor vector for each keypoint is 70-dimensional, with 64 dimensions provided by the SURF and 6 dimensions referring to the averages and the standard deviations of each color channel. All the other steps are performed as in BoVW.

D. Bag of Colors

The Bag of Colors (BoC) [10] is a color feature extractor that does not depend on a keypoint detector but somehow resembles the BoVW replacing the visual words dictionary with a color dictionary. Initially, the images are converted to the CIE-Lab color space which is more consistent with the Euclidean distance used by the k-means clustering technique used to build the color dictionary in BoC. Then, the next three steps are performed.

1) Color Dictionary: The BoC needs a color dictionary $C = \{c_1, ..., c_{k_c}\}$ defined as a set of k_c colors. First, each component **L**, **a** and **b** of the color space is quantized into 4 or 8 bins, making $k_c = 64(4\mathbf{x}4\mathbf{x}4)$ or $k_c = 512(8\mathbf{x}8\mathbf{x}8)$. Then, to create a dictionary adapted for a set of images from a specific domain and to reduce the impact of large areas with uniform color, the following steps are performed using a training set of images:

1) Resize each image to 256×256 pixels, convert them to the CIE-Lab color space and divide the image into 256 blocks of 16×16 pixels.
2) For each block, find the most frequent color and associate this color to the block. If the color found does not match at least 5 occurrences, value used to remove noise, a random color is chosen instead. In cases of ties between two or more most frequent colors, one is randomly chosen.
3) At this point, there are 256 colors for each of the N training images, i.e., $256 \times N$ colors and the K-Means algorithm is applied to cluster these colors in k_c groups.

A example of color dictionaries with $k_c = 64$ are presented in Figure 4.

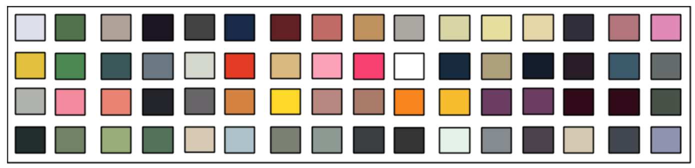


Fig. 4. Color dictionaries created by BoC with different sizes and using images of fishes in aquariums.

2) Feature Vector: Using the Euclidean distance, the pixels of new images are associated to one of the dictionary clusters and a frequency histogram is used to create a global feature vector for this image. Each image is first resized using isotropic scaling to a 16384 pixel image before the histogram creation.

3) Feature Vector Improvement: To improve the comparison of color histograms from different images, the Inverse Document Frequency (idf) normalization is performed, which decreases the contribution of the most common colors and increases the contribution of rare colors. This histogram was normalized using the power-law and the L1 vector normalization rule.

E. RGB and HSV Color Histogram

The last two techniques explored in this paper are the 3D color histograms in RGB and HSV color spaces. Given a color image, a 3D histogram is obtained by a requantization of each color channel (R, G, B and H, S and V) in a fixed number of bins and counting the occurring of each triple of color bins in the image pixels. In the experiments, the number of bins have been varied from 8, 16, 32 to 64 for each color channel. Thus, the size of the histogram varies from 512 (8^3), 4096 (16^3, 32.768 (32^3) to 262.144 (64^3).

F. Bag Of Colored Words

The Bag of Colored Words (BoCW) is a technique derived from BoVW and HSV color histogram which combines the features of both. Basically, for each image, feature vectors are extracted using BoVW and HSV color histogram. Subsequently, the vectors are concatenated joining the histogram color information with visual words from BoVW. This union was derived from previously analyzes where the HSV color histogram obtained good results. Thus, key points information has been added in order to improve the result of the HSV Color

Histogram and add color information to BoVW descriptors. Together with the attributes extractors mentioned, were used in the experiments four classifiers described in Section III-B.

III. Materials and Methods

In the experiments, the global image descriptors BoVW, BoC, BoFC, BoCW, HSV histogram and RGB histogram were compared using the image dataset described in Section III-A. The feature vectors were classified using three classifiers: Decision Tree, Support Vectors Machine(SVM) and k-Nearest Neighbors (KNN). These classifiers were chosen for its extensive use in the state-of-art. The performance of each descriptor was analyzed based on the F-Score metric and Area Under Rock. Statistical hypothesis test has been conducted using ANOVA, followed when applied, by Tukey post-hoc test. For all experiments were used cross validation with 10 folds and 10 repetitions. The images used in the experiments are detailed detailed below.

A. Image Dataset

The images that compose the AQUARIO28E40I dataset [1] has been taken with different smartphones, positions, at different places and different days. The dataset is composed by 40 photos for each of the 28 fish species. All of the species used in this work and their respective informations are illustrated on Figure 6. The photos of fish swimming freely were taken at a distance of about 1 meter with ambient lighting (Figure 5). The segmentation was done manually and in cases that there were more than one fish in the same picture, each fish was cutted to keep only one in each photo. The images were collected at the Municipal Aquarium of Toledo in Brazil [2] using three standard smartphones. Images obtained from fish stores[34] was taken using a Motorola Moto G[5].

B. Classifiers

The performance attributes of the extractors were compared using four classifiers: Decision Tree, Support Vector Machine (SVM) and k-Nearest Neighbors (KNN). Implementations of all classifiers were provided by Scikit-Learn [16].The classifiers are described below.

- Decision Tree [11], [17]: the decision tree is a machine learning algorithm belonging to the class of classifiers using supervised learning. It is used in regression and classification. The classification is given to create a model and predict the class of a sample by using decision rules infering the training set. Some advantages may be found in using the decision tree, such as: 1) simplicity in understanding its structure. 2) The cost of the tree use in predicting an example is logarithmic in the number of attributes used in the training set and 3) can be used in problems with multiple classes naturally.
- The SVM [18] is a supervised set of methods used for classification and regression. SVM's Classifiers are based on a maximum margin between classes to classify

Fig. 5. Image of the Municipal Aquarium of Toledo, Paraná, Brazil.

Image	Popular Name	Cientific Name
	Dourado	Salminus brasiliensis (Cuvier, 1816)
	Acará Bandeira	*Pterophyllum scalare (*Schultze, 1823)
	Tetra Negro	*Gymnocorymbus ternetzi* (Boulenger, 1895)
	Platy Ruby	*Xiphophorus maculatus* (Günther, 1866)
	Telescópio	*Carassius auratus* (Linnaeus, 1758)
	Paulistinha	*Danio rerio* (Hamilton, 1822)
	Peixe Papagaio	*Sparisoma chrysopterum* (Bloch e Schneider, 1801)
	Oscar Albino	*Astronotus ocellatus* (Agassiz, 1831)
	Mato Grosso	Hyphessobrycon eques (Steindachner, 1882)
	Platy Laranja	*Xiphophorus maculatus* (Günther, 1866)
	Peixe Palhaço	*Amphiprion frenatus* (Brevoort,1856)
	Kinguio Karraco	*Carassius auratus* (Linnaeus, 1758)
	Kinguio Cometa Calico	*Carassius auratus* (Linnaeus, 1758)
	Barbus Sumatra	*Puntigrus tetrazona* (Bleeker, 1855)
	Barbus Ouro	*Puntius sachsii* (Ahl, 1923)
	Acará Disco	*Symphysodon aequifasciatus* (Pellegrin, 1904)
	Oscar	*Astronotus ocellatus* (Agassiz, 1831)
	Tricogaster	*Trichogaster trichopterus* (Pallas, 1770)
	Kinguio	*Carassius auratus* (Linnaeus, 1758)
	Platy Sangue	*Xiphophorus maculatus* (Günther, 1866)
	Molinésia Preta	*Poeclia shenops* (Valenciennes, 1846)
	Carpa	*Cyprinus carpio* (Linnaeus, 1758)
	Beta	*Betta splendens* (Regan, 1910)
	Tucunaré	*Cichla ocellaris* (Bloch e Schneider, 1801)
	Piau Três Pintas	*Leporinus friderici* (Bloch, 1794)
	Pacu	*Piaractus mesopotamicus* (Holmberg, 1887)
	Acará Bandeira Marmorizado	*Pterophyllum scalare (*Schultze, 1823)
	Carpa Média	*Cyprinus carpio* (Linnaeus, 1758)

Fig. 6. Illustration of all fish species used in this work with its popular and scientific names.

[1] http://pistori.weebly.com/datasets.html

[2] http://www.toledo.pr.gov.br/portal/meio-ambiente/aquario-municipal-romolo-martinelli.

[3] Planeta Real, Av. Afonso Pena, 1919 - Centro, Campo Grande - Mato Grosso Do Sul. Telefone: (67) 3025-4942.

[4] Peixinho Dourado, Av. Marechal Rondon, 1338, Centro, Rondonópolis, Mato Grosso

[5] http://www.motorola.com.br/Moto-G-da-Motorola/Moto-g-gen2-br.html

new examples, and maximizing the margin, improves the generalization at the classification stage. The separation of the classes can be done by linearly or polynomially kernels, depending of the dataset used. Some advantages can be found in the use of classifiers based on support vector machines [16]: 1) it is very effective in large dimensional spaces, that is, when the amount of attributes for the problem approached is large, 2) it still effective even in cases where the number of dimensions is larger than the examples, 3) Different kernels can be specified as decision functions become a versatile SVM classifier. If necessary, it is possible to set a customizable kernel.

- K-Nearest Neighbors - (KNN): the principle of KNN is associated with finding a predefined number of neighbors in training set of a new example and rank it. The majority class among neighbors classifies the new instance. 1) The KNN has as one of its main advantages simplicity, plus a quick learning phase, it get good results in several problems.

C. Dictionary Size

To determine the suitable dictionary size k to represent the characteristics of fishes, the following values were evaluated for BoVW, BoFC, BoCW and BoC: 64, 128, 256, 512, 1024, 2048, 4096 and 8192. These values were varied in this way following the variations found in literature reviews. Since RGB and HSV histogram are not based on the BoVW, the number of bins for both descriptors was varied from $8^3, 16^3, 32^3, 64^3$. The minimum number of bins evaluated was 8 (512 attributes) due to the considerable loss of color information for smaller values. On the other hand, the maximum number of bins was 64 (262.144 attributes) due to limitations of the hardware used in the experiments. For each dictionary parameters of the classifiers were varied according to the description of Section III-D.

D. Parameters of the Classifiers

The parameters of the classifiers were varied as follows:

- Decision Tree: as each node of the tree split strategy, the best division or a random was used. The division criterion was also varied between entropy and "gini" to impurity Gini.
- SVM:linear and RBF cores were used. According to Chang et al. [19] linear core has better performance for a training set with lots of attributes, fitting in the context of this work. The RBF core can better adapt to certain sets of training non-linear attributes, and thus, it was inserted in the experiments.The values of C and γ were mixed in logarithmic space corresponding to the values: from $\log_2^{-5}$ to $\log_2^{15}$ for C values and $\log_2^{-15}$ to $\log_2^{3}$ for γ.
- KNN: the K value was varied from 1 to 500 incrementing by one unit. The metrics used to calculate the distance of the points also varied. The uniform metric and the inverse distance was used, ie, closest points have greater weight in the classification.

IV. Experiments

1) Support Vector Machine - SVM: The SVM has been tested with the following kernels: Normalized Polynomial, Polynomial, RBF and Puk. For each kernel, the parameter c was varied as follow: 1, 5, 10, 15, 20 and 25. According to the results, the BoC, BoFC, RGB and HSV histograms obtained the highest F-Score using polynomial kernel with $c = 25$. The BoVW achieved the highest F-Score using normalized polynomial kernel with $c = 5$.

2) K-Nearest Neighbors - KNN: The main parameter of the KNN is the number of neighbors K, which is evaluated in Table I. As can be seen, most of the global image descriptors obtained the highest F-Score for $K = 3$. However, the BoVW and BoFC obtained the best result for $K = 13$ and $K = 5$, respectively.

TABLE I
KNN F-Scores

Extractor	$K=3$	$K=5$	$K=7$	$K=9$	$K=11$	$K=13$
BoVW	0.324	0.321	0.286	0.309	0.302	**0.331**
BoC	**0.807**	0.793	0.774	0.765	0.75	0.53
BoFC	0.596	**0.603**	0.6	0.553	0.531	0.53
HSV H.	**0.877**	0.834	0.823	0.803	0.777	0.768
RGB H.	**0.826**	0.799	0.76	0.753	0.748	0.729

3) Decision Tree - C4.5: For the C4.5 classifier (implementation of J48), the following parameters were evaluated: confidence factor c varying between 0.2 and 0.3 and the number of instances per leaf n_{min} ranging from 2 to 4. For BoVW, BoC, HSV and RGB histograms, the highest F-Score was obtained for $c = 0.2$ and $n_{min} = 3$, with F-Scores equal to 0.466, 0.842, 0.837 and 0.823, respectively. For BoFC, the highest F-Score of 0.823 was obtained using $c = 0.3$ and $n_{min} = 4$.

V. Results and Discussion

In this section, the global image descriptors are compared using the settings that provided the highest F-Score as described in the previous section. Table II shows that the SVM classifier provided the highest F-Score for all descriptors. Using SVM, ANOVA statistical test has been conducted to compare the descriptors.

TABLE II
Comparison of F-Score of each classifier.

Extractor	C4.5	KNN	SVM
BoVW	0.466	0.331	**0.713**
BoC	0.842	0.807	**0.923**
BoFC	0.662	0.603	**0.873**
HSV Color Histogram	0.842	0.877	**0.941**
RGB Color Histogram	0.823	0.826	**0.926**

Figure 7 shows a boxplot of the F-Scores obtained by each descriptor with the same classifier, SVM. We can observe that RGB and HSV histograms achieved the highest F-Scores, followed by the BoC descriptor. These three descriptors achieved F-Scores above 0.9 for our dataset of fish species. To compare the performance of each classifier using the parameters described below, the cross validation was applied with 10 folds and 10 repetitions across the dataset.

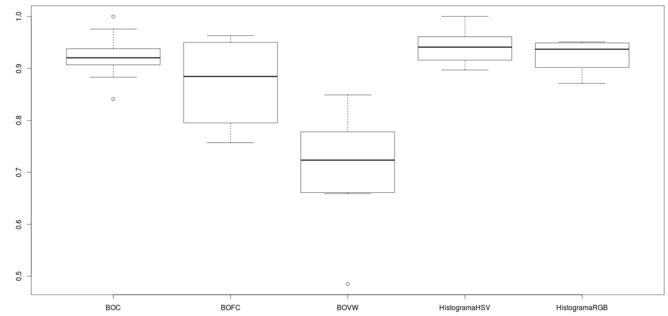


Fig. 7. Boxplot of the five descriptors F-Scores using the same SVM classifier.

We also performed the ANOVA test ($p = 4.3e^{-10}$) followed by the Tukey post-hoc test. The pair-wise comparison can be seen in Table III. According to the comparisons, it is observed that all descriptors that include color are statistically superior to the BoVW.

TABLE III
TUKEY TEST.

Extractors	BOFC	BOC	HSV H.	RGB H.
BoVW	**0.0000101**	**0.0000000**	**0.0000000**	**0.0000000**
BoFC	•	0.4199019	0.1456418	0.3662707
BoC	•	•	0.9714866	0.9999810
HSV H.	•	•	•	0.9845542

Finally, Table IV illustrates the confusion matrix from the results of the HSV histogram descriptor. It can be observed that four images from Piau Trê Pintas species were incorrectly classified as Tucunaré. From Figure 8, we can see that both species have similar colors. The other misclassified images are from species with similar colors or they became similar due to the influence of local lighting.

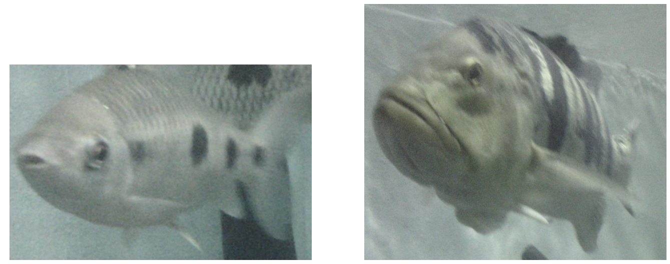
TABLE IV
CONFUSION MATRIX FOR THE CONFIGURATION THAT ACHIEVED THE HIGHEST F-SCORE: SVM + HSV COLOR HISTOGRAM.

a	b	c	d	e	f	g	h	i	j	Classified as
39				1						a-Acará Bandeira
3	37									b-kinguio
3		37								c-Molinésia Preta
			40							d-Platy Sangue
2		1		37						e-Tricogaster
					39			1		f-Dourado
						39			1	g-Oscar
					3	1	35	1		h-Pacu
					1			35	4	i-Piau Três Pintas
					1			1	38	j-Tucunaré

VI. CONCLUSION

The use of color in global image descriptors proved to be of great value to improve the accuracy of fish image classification. In this work, the descriptors that used color in the image description provided better results than the BoVW, a descriptor that uses only brightness information. In real situations, the model and datasets could be stored in a server, to a mobile phone make requests and recieve responses about the classification.

In classifications where only colors are used to describe the images, the results are satisfactory, with F-Score values of 0.923, 0.926 and 0.941 for BoC, RGB color histogram and HSV color histogram, respectively. The images used in this work have been improved (clippings were made around the fish) to be better described. In images obtained without treatment (cropping, lighting adjustments) the amount of noise increases, as well as variations in illumination, damaging the classification using only colors. Besides that we also have a satisfactory result compared to the related papers presented, since this work perform the fish species classification with a larger dataset than those presented.



(a) Piau Três Pintas (b) Tucunaré

Fig. 8. Color similarity between images.

VII. ACKNOWLEDGEMENTS

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