

UNSUPERVISED COLOR TEXTURE FEATURE EXTRACTION AND SELECTION FOR SOCCER IMAGE SEGMENTATION

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ABSTRACT

In this paper, we describe a new approach for color texture feature extraction and selection. We define color texture features as texture features which are computed by taking into account the color components of the pixels. We determine the most discriminating color texture features among a multidimensional set of color texture features by means of an iterative feature selection procedure associated to an information criterion. This procedure analyses images which are classified by a competitive learning scheme. Soccer image segmentation is achieved by pixel classification. The classification algorithm takes into account these color texture features which are processed in the neighborhood of the pixels. We apply our new unsupervised approach to soccer images segmentation.

1. INTRODUCTION

In the framework of soccer players tracking, we propose an original color image segmentation method which consists in the classification of *player pixels*, that is to say, the pixels which represent the players [1, 2]. We suppose that the team of each player is identified by the color and the texture of its soccer suit. So, the player pixels belonging to players with the same soccer suit constitute one class of player pixels. We can consider five different classes namely the players of the two teams, the two goalkeepers and the referees. Because the soccer players suits are colored and textured, we consider several texture features associated to different color components.

Each player pixel is classified according to its *color texture features* values [3]. A color texture feature is a texture feature (mean, standard deviation, skewness...) which is computed by taking into account the color components of its neighbor pixels ($R, G, B, L^*, a^*, b^*, Y, I, Q...$). So, we use a set of N_t texture features associated to a set of N_c color components. We construct a representation space by considering that each player pixel is represented by a point whose coordinates are the $N_c \times N_t$ color texture features.

The automatic player pixels classification requires a very large computation time since the dimension of the color texture feature space is $N_c \times N_t$. The computational burden is reduced by projecting the color texture feature space onto a lower dimensional space thanks to the selection of the most discriminating color texture features.

1.1. The previous supervised approach

In order to determine this space, we require a set of observations that we choose tanks to a supervised learning scheme. Indeed, from learning images, we interactively select player pixels which belong to each class. That permits us to determine the most discriminating color texture feature space thanks to an iterative feature selection procedure associated to an information criterion.

1.2. The new unsupervised approach

In this paper, we propose an unsupervised learning scheme which automatically determines the set of observations by analysis of learning images. These observations are player pixels which are extracted thanks to the well known *competitive learning* algorithm [4]. These player pixels are analysed by the most discriminating color texture feature selection scheme.

1.3. Scheme

In the second section of this paper, we present the unsupervised selection of the most discriminating color texture features. In the third section, we describe the pixel classification algorithm which assigns each player pixel to a class according to the values of the color texture features of its neighborhood. We apply our previous supervised approach and our new unsupervised approach to a soccer image and we compare the results.

2. UNSUPERVISED COLOR TEXTURE FEATURE SELECTION

In order to determine the color texture feature space, we require observations which are representative of the N classes of player pixels C_j ($j = 1, \dots, N$). These observations are player pixels which are classified by competitive learning [4]. They are used by a classical multiple discriminant analysis method in order to select the most discriminating color texture feature space.

2.1. Color texture features

A player pixel can be characterized by color texture feature values which are computed by taking into account the color components of the neighbor player pixels.

Here, we use a non exhaustive list of texture features. The *mean* of the pixel values in a neighborhood, the *median* and the *mode* evaluate the central value of this neighborhood. The variability of the pixel values around a central value is estimated by the *variance* or its square root, the *standard deviation*. The *skewness* estimates the degree of asymmetry of the pixel values around a central value. The variance and the skewness can be evaluated around the mean, the median or the mode. Let N_i , be the number of available texture features which are computed with one color component.

The pixels of a color image are usually digitized with the (R, G, B) color representation system which is not always adapted to a specific problem of color image segmentation. In digital color imaging, many other color representation systems exist [5]. For our study, we use the more classical color representation systems which are derived from the (R, G, B) system, such as: the primaries system CIE (X, Y, Z) , the normalized systems (R_n, G_n, B_n) and CIE (X_n, Y_n, Z_n) , the Ohta's system $(I1, I2, I3)$, the Faugeras's system $(A, C1, C2)$, the Ballard's system (wb, rg, by) , the television systems (Y', I', Q') and (Y', U', V') , the perceptually uniform systems CIE (L^*, a^*, b^*) and CIE (L^*, u^*, v^*) and different perceptual systems (L, C, H) . There is a total of N_c available color components which constitute the different above mentioned color representation systems.

By taking into account the $N_f = N_c \times N_i$ available color texture features, we define an N_f -dimensional color texture feature space. The large dimension of this space inevitably generates redundancy. Furthermore, the classification algorithm is very costly in computation time. So, our goal is to look for the best subset of color texture features for discriminating the different classes of pixels.

2.2. Unsupervised observation selection

The set of observations, i.e. the player pixels which represent the classes, are automatically extracted from a *presegmented learning image*.

In this image, the ground is withdrawn thanks to an adapted Ohlander's algorithm in order to extract the player pixels [6] (see figure 1).

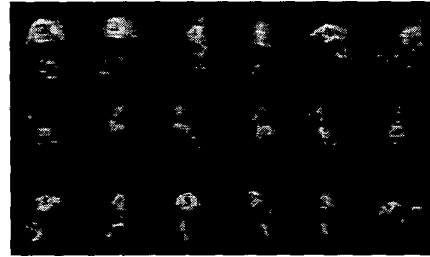


Fig. 1. Presegmented learning image

Then, the player pixels are represented by three color texture features which are the mean values of the components R , G and B of their neighbors. They are assigned to the classes thanks to the competitive learning scheme (see figure 2).

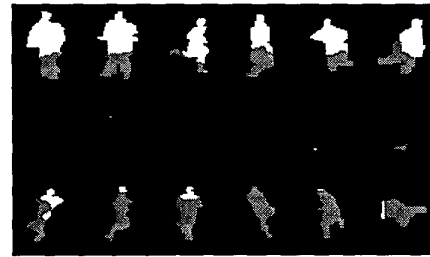


Fig. 2. Classified player pixels by competitive learning

A blob analysis merged together the classified player pixels in order to construct regions which correspond to players. The regions whose the surface area is the highest one are retained. Thus, the player pixels which belong to these regions form the set of N_Ω observations ω_i ($i = 1, \dots, N_\Omega$). The player pixels which are assigned to the class C_j form a set of N_j observations. These observations are used to determine the color texture feature space which yields the best separation between the classes.

2.3. The most discriminating color texture feature space

In order to reduce the dimension of the color texture feature space, we use an iterative feature selection procedure which determines the most discriminating color texture features [3]. At each step of this procedure, we consider several candidate color texture feature spaces for which we compute their discriminating power thanks to an information criterion J . The procedure is iterated until stabilization of the value of J . Let k_0 , be the rank of the iteration process which corresponds to the beginning of the stabilization of J . k_0 is

the dimension D of the color texture feature space. This method does not yield the optimal solution but a satisfying one which is less computation time consuming.

The evaluation of the discriminating power supposes that the more the classes are well separated and compact in the candidate color texture feature space, the higher the discriminating power of the selected features is. That leads us to choose measures of classes separability and compactness as measures of the discriminating power.

At each step k of the selection procedure and for each of the $(N_f - k + 1)$ k -dimensional candidate color texture feature spaces, we define, for each observation ω_i , a *color texture feature vector* $X_i = [x_i^1, \dots, x_i^k]^T$ where x_i^k is the k^{th} color texture feature.

The measure of compactness is defined by the intra-class dispersion matrix Σ_C :

$$\Sigma_C = \frac{1}{N_\Omega} \times \sum_{j=1}^N \sum_{\omega_i \in C_j} (X_i - M_j)(X_i - M_j)^T$$

where $M_j = [m_j^1, \dots, m_j^k]^T$ is the *mean vector* of the k color texture features of the N_j observations of the class C_j .

The measure of the class separability is defined by the inter-class dispersion matrix Σ_S :

$$\Sigma_S = \frac{1}{N_\Omega} \times \sum_{j=1}^N N_j \times (M_j - M)(M_j - M)^T$$

where $M = [m^1, \dots, m^k]^T$ is the mean vector of the k color texture features of the N_Ω observations.

The most discriminating color texture feature space maximizes the information criterion:

$$J = \text{trace}\left((\Sigma_C + \Sigma_S)^{-1} \Sigma_S\right).$$

In order to only select features which are not correlated, we measure, at each step $k \geq 2$ of the procedure, the correlation between the candidate color texture feature and each of the $k - 1$ other color texture features constituting the considered space. An *observation vector*, denoted $X^f = [x_1^f, \dots, x_i^f, \dots, x_{N_\Omega}^f]$ is associated to each color texture feature. The correlation $\text{cor}(X^f, X^{f'})$ between two features is defined by:

$$\text{cor}(X^f, X^{f'}) = \frac{\text{cov}(X^f, X^{f'})}{\sigma^f \times \sigma^{f'}}$$

where $\text{cov}(X^f, X^{f'})$ is the covariance between the two features:

$$\text{cov}(X^f, X^{f'}) = \sum_{i=1}^{N_\Omega} \frac{(x_i^f - m^f) \times (x_i^{f'} - m^{f'})}{N_\Omega}$$

and σ^f is the standard deviation of the candidate color texture feature for all the classes and m^f is the mean of the candidate color texture feature for all the classes.

The correlation value ranges between 0 and 1. The closer is the correlation to 1, the more correlated the two features are. If one of the computed correlation is higher than the value 0.75, the candidate color texture feature is rejected.

Thanks to this iterative procedure, we select the set of the most discriminating color texture features among the N_f available ones.

3. SOCCER IMAGE SEGMENTATION

In order to classify a player pixel P , we compute its color texture feature vector $X_P = [x_P^1, \dots, x_P^D]^T$ in the above determined D -dimensional color texture feature space. For that, we consider the set of the neighbor player pixels falling into a neighborhood of P (see figure 3). This neighborhood is defined by a *neighborhood window* which is centered on the player pixel P and whose the size depends on the mean size of the players.

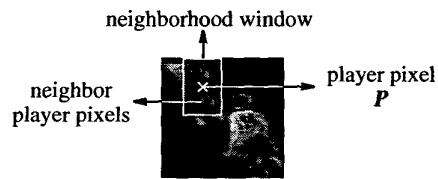


Fig. 3. Player pixel neighborhood

For each class C_j , we evaluate the euclidean distance D_j^P between X_P and the mean vector $M_j = [m_j^1, \dots, m_j^D]^T$ of the class C_j in the D -dimensional color texture feature space. A minimum distance decision rule is used to assign P to the class C_j for which D_j^P is minimum.

In order to compare the unsupervised and supervised approaches, we choose a learning image (see figure 1) and a test soccer image (see figure 4) which contains three different classes of player pixels.

The determined color texture feature space by our previous supervised approach is a 4-dimensional one and is constituted by the mean value of the a^* color component of the system (L^*, a^*, b^*) , the mean value of the chroma color component of the system (Y', U', V') , the standard deviation around the median associated to a saturation color component and the skewness around the mean associated to the L^* color component of the system (L^*, a^*, b^*) [3]. By reading the confusion matrix (see table 1), we conclude that the mean classification error rate is lower than 2%.

We apply our new unsupervised approach. The determined color texture feature space is a 4-dimensional one and

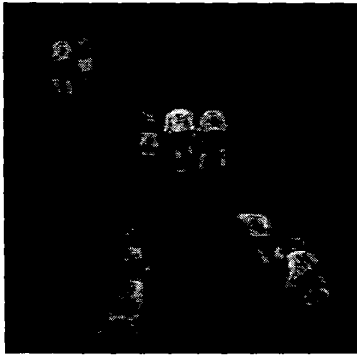


Fig. 4. Test image

	C_1	C_2	C_3
C_1	97.51 %	1.40 %	1.09 %
C_2	0.12 %	98.67 %	1.21 %
C_3	0.12 %	0.00 %	99.88 %

Table 1. Supervised approach confusion matrix

is constituted by the mean value of the chroma color component of the system (Y', U', V') , the mean value of the u^* color component of the system (L^*, u^*, v^*) , the skewness around the median associated to a saturation component and the standard deviation around the median associated to the hue color component of the system (Y', I', Q') . The image of the figure 5 represents the classified pixels in this space by our classification algorithm. The confusion matrix shows

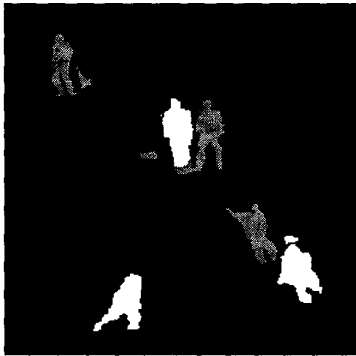


Fig. 5. Unsupervised approach results

that the player pixels are correctly assigned with a mean error rate lower than 5 % (see table 2).

In this case, the unsupervised approach provides wrong results than the supervised one. Other cases which have been tested, show the influence of the choice of learning im-

	C_1	C_2	C_3
C_1	93.43 %	3.40 %	3.17 %
C_2	0.12 %	92.92 %	6.96 %
C_3	0.12 %	0.42 %	99.46 %

Table 2. Unsupervised approach confusion matrix

ages to the color texture feature selection. Indeed, we must carefully select the learning images so that each player is isolated and their neighborhood don't overlap each other.

4. CONCLUSION

The new color image segmentation approach proposed here shows the contribution of color texture features to unsupervised pixels classification. The unsupervised approach results are closed to the supervised approach results and, in the two cases, the color texture feature spaces are very similar. So, the unsupervised approach can be applied to the soccer player tracking by color image sequence analysis [2].

5. REFERENCES

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