Features analysis and Fuzzy-SVM classification for tracking players in water polo

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Abstract: - This paper presents a novel approach for detection and tracking humans in water. Uniqueness of the tracked objects has been defined after analysis of standard color models. Based on the analysis results, YCbCr is proposed as the best color model for targeted application. Furthermore, relation of Cb and Cr components for different categories of targeted objects (object parts) were analyzed and used as features that can be used by classifier. Fuzzy-SVM classifier is proposed as the best solution for particular domain of problems. Unlike other Fuzzy-SVM methods, presented method is focused on fuzzy logic and applies binary SVM only in special situations when classification of input data is uncertain. In order to test and evaluate hypothesis, proposed method was compared to standard classification methods. Experimental results demonstrated validity and efficiency of the proposed approach.

Key-Words: -Fuzzy SVM,YCbCr, classification, water polo, tracking player, feature extraction

1 Introduction

Tracking humans in water is very challenging and difficult task. In computer vision, uniqueness is the most desirable property so that the object can be easily distinguished in feature space. Depending on the application domain, some authors [1] use color, edges, optical flow or texture as common visual features. Because of water splashing and illumination variations on the water surface, swimmers can be regarded as moving objects in dynamic environment. As swimmer shape is changeable, use of colors, edges, optical flow or texture is not suitable for tracking in water domain. In swimmer tracking framework [2] authors adopted Gaussian mixture model to represent the background and swimmers. In order to reduce the influence of illuminationchanges, they used HSV color space. Related pixels were grouped by mean-shift clustering algorithm. Some authors used HSI color space for development of drowning detection systems[3].Also, a part of the previous research related to detection of waves and objects in water was focused on dynamic textures[4],but problem of swimmers affecting background while swimming was not addressed. Furthermore, the same problem rises with edge detection and optical flow. Thus, there is no constant shape of player and background has significant variations during the game.

Many authors have tried to find the color space that can be applied for their specific object color segmentation problem. In [5] authors presented the integration of distributions in RGB space into particle filtering. Evaluation results in [6] have indicated that YCbCr and HSV color spaces have better tracking ability compared to the use of grayscale and RGB color spaces for different tracking methods. These results has also indicated that data from selected layers in some color spaces can be used for the purpose of tracking namely the Cb and Cr layers from the YCbCr color space and the H layer from the HSV color space. Use of HSV color space is a subject of numerous papers[7]. In [8] Hue and Saturation values are used to populate HS histogram. For tracking hockey players, multi-color observation model based on Hue Saturation and Value color histogram is adopted[9]. Method for classifying color points for automotive applications in the Hue Saturation Intensity (HSI) space based on the distances between their projections onto the SI plane is presented in [10]. Since HSV decouples the intensity from color, it is reasonably insensitive to illumination effect and has wide range of applications.

The experimental results in [11] shows that the fusion method provides feature detection results having a higher discriminative power than the standard weighting scheme. Authors of this paper proposed a method that exploits non-perfect correlation between color models or feature detection algorithms derived from the principles of diversification to find proper color model selection and fusion of feature detection algorithms. Some other authors like [12] and [13] use hybrid color space and fusion procedure which aims at combining several segmentation maps associated to simpler partition models in order to finally get a more reliable and accurate segmentation result.

Segmentation is one of the most important problems in color image analysis. Each segmentation region consists of pixels, so the problem of extracting features can also be considered as a pixel classification. Regardless of color model that is selected to extract features, it is important to select appropriate classification method. Selection of the classification method depends on application. Usually, ratio is between accuracy and speed. In some cases, when accuracy is most important, slow but accurate methods can be applied. If the speed is more important, like in real-time systems it is much more important to create predefined classifiers. In the past, fuzzy rule based systems have been applied to control problems, but recently they have also been used in pattern [14] and image [15]classification tasks. One of the fast classification methods is support vector machine (SVM) which is formulated for two-class classification problems. Also, there are several ways to extend this method for multiclass problems, but basic methods are one-against-one method (1A1) and one-against-all method (1AA).According to comparative study [16], two 1A1 classification method give better results than 1AA method and in [17] is noticed that with large number of classes, 1A1 method is faster and more accurate.

Some authors proposed combination of Fuzzy logic and SVM method attempting to improve the classification accuracy and generalization. Fuzzy-SVM methods presented in [18], [19] and [20] apply fuzzy membership to each input point of SVM and we can say that authors improve SVM method with Fuzzy logic. Our idea is to improve Fuzzy logic classifier with SVM.

In this paper,we consider two problems. First, we analyze various color models, discuss and propose set of features for applications dealing with object tracking in water-related environment. Second, we propose classification method that combines Fuzzy logic and SVM method. Unlike other Fuzzy-SVM methods, presented method has focus on Fuzzy logic and applies binary SVM in special situations when classified input data can belong to more than just one class.

2 Problem formulation

To the best of our knowledge, there is no computer vision application for tracking water polo players. The closest papers and applications are vision-based swimmer tracking [2], human detection in aquatic environment [21] and drowning detection systems [22]–[24]. It is possible to use some fragments of mentioned works, but there are major differences. Unlike swimmer tracking, in water polo there are occlusions and overlaps. There is more than one player and it is important to determine the best way to extract features for afterwards tracking. Unlike football, basketball or handball tracking[25], in water polo there are some aggravating circumstances:

- Background is changeable because of water motion
- Water reflects light, so illuminationaffects the background
- Player shape is changeable. Unlike some other sports, self-occlusions are possible

In water polo, player cannot be described with one shape or one color. The same player can be different in different positions depending if he is swimming or floating still. For our problem, we decided to engage human observer to analyze water polo game and extract features that describe one player in every situation. Our observer single out following objects and state features: cap color, player number, player body, splashing, expected player position, changeable background around player.

Based on problem analysis, four main appearance categories were defined.

1) Swimming pool
2) Player caps
3) Player body
4) Splashing

Player’s appearance can be described using combination of three categories (cap, body and splashing). Swimming pool category can be used as known or expected background.

Based on results in [26] for object classification in water sports and the results presented in [27][28] for skin color segmentation as well as the results in[2][24] for detecting people in swimming pool we concluded:

- It is possible to create data class for each chosen category (based on analysis of each category).
- HSI and YCbCr color models have separated illumination component, so they should yield better results in segmenting objects in water than RGB color model.

- Features for tracking descriptor can be obtained by combining one or more categories (Figure 1).

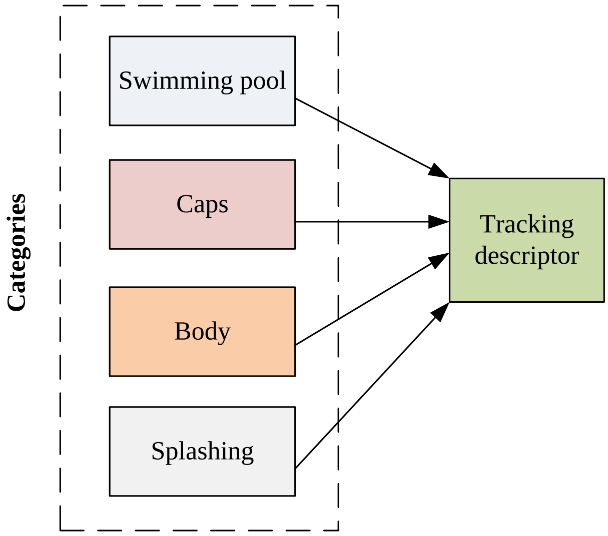

Fig.1 Tracking descriptor

2.1 Category extraction

The training sets were carefully manually selected in order to represent a common picture set of each class. Supervised classification [29] was adopted for category classification and to creation of descriptors for each class based on training sets of object images. Expert knowledge of the domain was used to extract each part of the scene. Expert of the domain was employed in order to annotate objects using LabelMe[30] annotation tool (Fig. 2).

From a set of 10000 test images, expert selected 100 templates for each category as shown on Figures3, 4, 5 and 6.

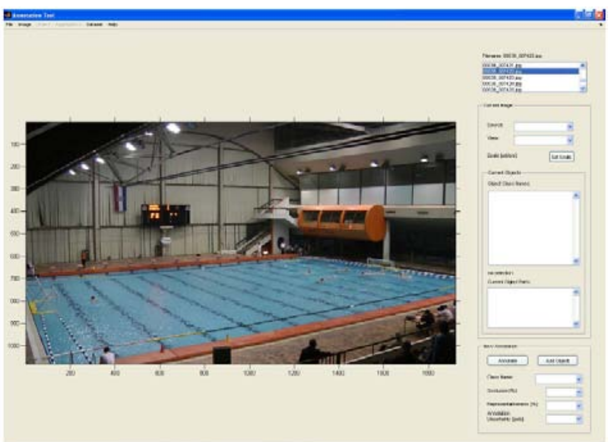

Fig.2 LabelMe annotation tool

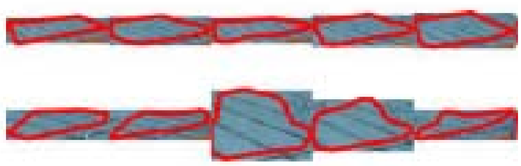

Fig.3 Annotated swimming pool area

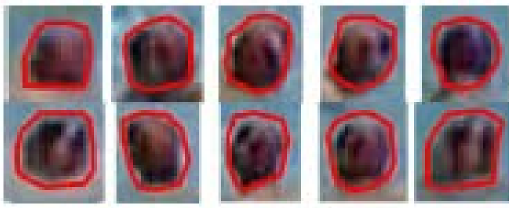

Fig.4 Annotated caps area

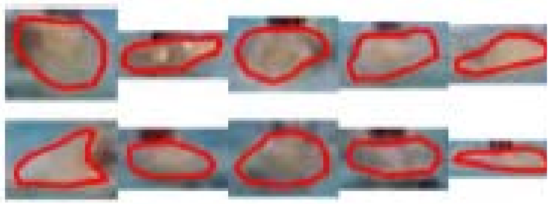

Fig.5 Annotated player body area

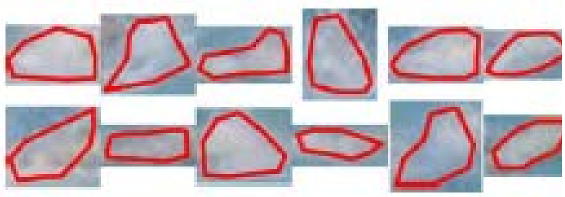

Fig.6 Annotated splashing area

2.2 Color models analysis

For optimal color model selection, each category was analyzed in RGB, YCbCr and HSI color model.

2.2.1 Swimming pool

Blue color dominatesin swimming pool category, as it can be seen from RGB histogram. Analyzing YCbCr histogram (Figure 7), it can be seen that Cb and Cr components have very thin distribution and all Cr values for this category are smaller than Cb values. As the values of HSI histogram showed more overlapping, conclusion was made that Cb and Cr components of YCbCr color model will be used for testing and experiment.

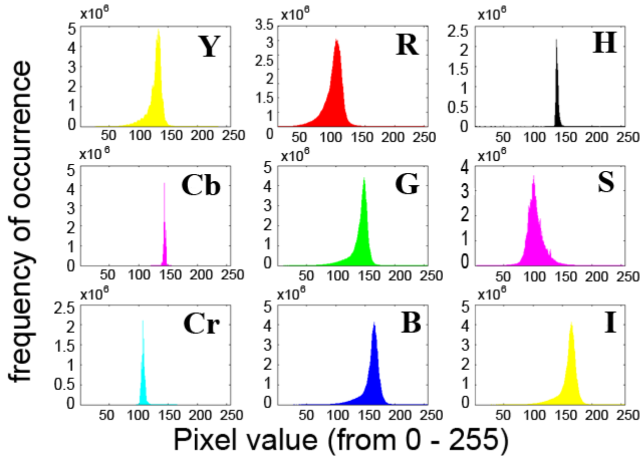

Fig.7 Y, Cb, Cr, R, G, B. H, S and I histogram of swimming pool category (pixel value vs. frequency)

2.2.2 Caps

For cap analysis, one team caps has been selected and extracted. It is rather hard to create unique model for cap area because they can be different in size and color, with numbers or even mixed with water, splashing and skin color. From the histogram presented in Fig. 8, it is evident that, again,Cb and Cr areas have the thinnest distributions.

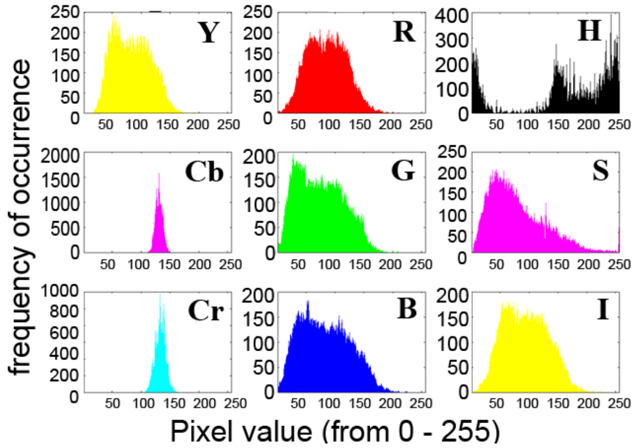

Fig.8 Y, Cb, Cr, R, G, B. H, S and I histogram of Cap category(pixel value vs. frequency)

2.2.3 Player body

In water polo, player body is usually covered with water, but it is close to pool surface, so it can be recognized. The thinnest registered distribution of skin area is also inCb and Cr histogram (Figure9). Skin segmentation results are expected, as YCbCr color model gives very good results for the skin segmentation problem [28], [31].

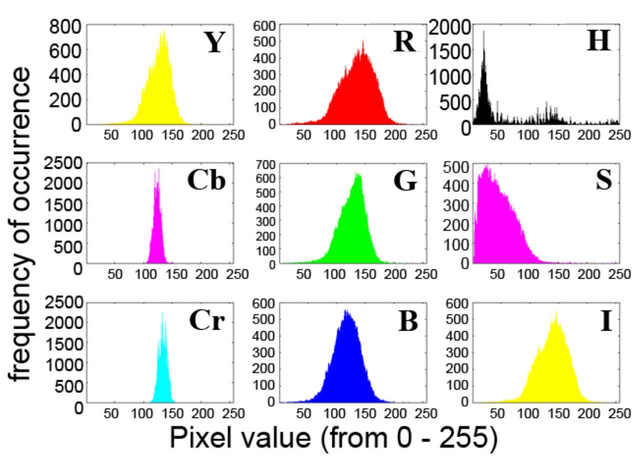

Fig.9 Y, Cb, Cr, R, G, B. H, S and I histogram of player body category(pixel value vs. frequency)

2.2.4 Splashing

On splashing comparison histogram(Figure 10), Cb and Cr components are also the thinnest; intensity components of HSI an YCbCr color model are expected more emphasizedand thinner than in other category histograms.

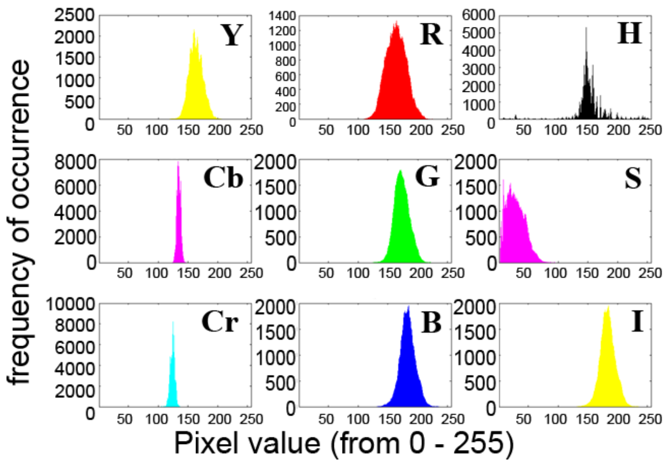

Fig.10 Y, Cb, Cr, R, G, B. H, S and I histogram of Splashing category(pixel value vs. frequency)

2.2.5 Color models values analysis

Based on categories histograms analysis and results in [28], [31], [32] we decide to further analyze YCbCr and HSI color model for our problem. From each histogram, it is evident that Cb and Cr component in YCbCr color model are thinnest, so it can be expected that it is possible to describe each category with dependency between these two components. Comparison with H-S dependence has also been done. Results are shown in Figure 11 and Figure 12.

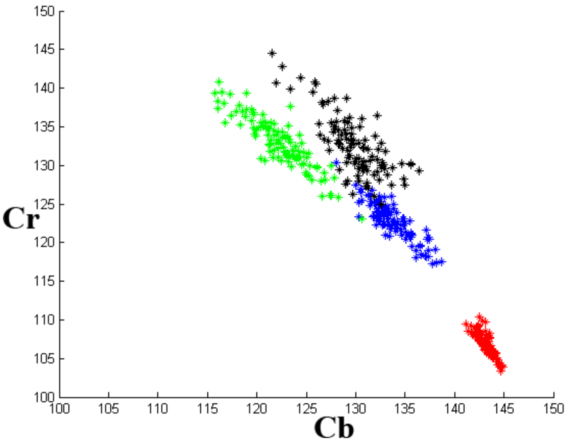

Fig.11 Cb-Cr relation category distribution

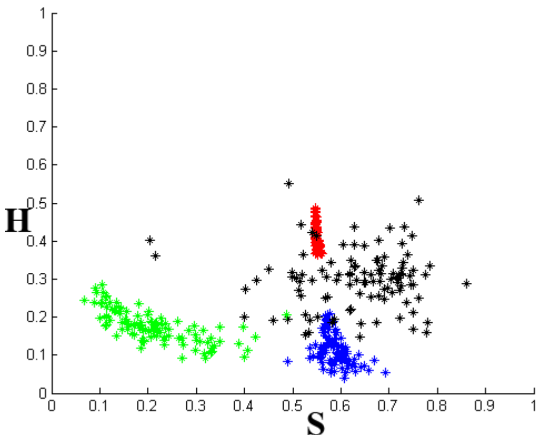

Fig.12 H-S relation category distribution

Red dots represent swimming pool category mean value for each template. Blue dots represent splashing category mean value. Black dots represent cap category mean value and green dots represent body templates mean value. As is evident from Figures 11 and 12 categories mean values are more properly distributed in Cb-Cr relation than in H-S relation.

Table 1 Values for swimming pool category (Cb, Cr values range: 16-240; H, S values range: 0-1)

	Cb	Cr	H	S
Min. pixel value	141,216	103,4204	0,5463	0,3635
Max pixel value	144,85	110,4235	0,5604	0,869
Difference	3,634	7,0031	0,0141	0,5055
Total difference	1,43%	2,75%	1,41%	50,55%

Table 2 Values for cap category (Cb, Cr values range: 16-240; H, S values range: 0-1)

	Cb	Cr	H	S
Min. pixel value	121,49	122,95	0,2032	0,1485
Max. pixel value	136,4	144,53	0,8605	0,552
Difference	14,91	21,58	0,6573	0,4035
Total difference	5,85%	8,46%	65,73%	40,35%

Table 3 Values for splashing category (Cb, Cr values range: 16-240; H, S values range: 0-1)

	Cb	Cr	H	S
Min. pixel value	128,048	117,266	0,4897	0,04
Max. pixel value	138,73	130,35	0,6917	0,2101
Difference	10,682	13,084	0,202	0,1701
Total difference	4,19%	5,13%	20,20%	17,01%

Table 4 Values for body category (Cb, Cr values range: 16-240; H, S values range: 0-1)

	Cb	Cr	H	S
Min. pixel value	115,75	123,12	0,069	0,0918
Max. pixel value	130,59	140,85	0,4867	0,2858
Difference	14,84	17,73	0,4177	0,194
Total difference	5,82%	6,95%	41,77%	19,40%

Furthermore, each category area was analyzed and results are presented in tables 1-4. Minimum pixel value is minimum value of pixel for each category. Maximum pixel value is maximum value of pixel for each category. Difference is the biggest difference between minimum and maximum values of pixels. As Cb and Cr values are in the range from 16 to 240 and H and S are in range from 0 to 1, Total difference in tables 1-4 is percentage value in relation to range of each color component.

Based on Figure 11 and Total difference values from tables 1-4, it can be concluded that Cb-Cr relation should be preferred for classification of swimming pool, splashing, body and cap pixels.

2.3. Fuzzy-SVM classification method

There are a lot of classification methods that can be used in machine learning systems[33], [34]. Based on quantity of learning data, type of classification accuracy and classification speed it is important to chosean appropriate method for particular task. For our application problem, decision was made to focus on Support Vector Machines and Fuzzy classifier in order to achieve fast and accurate classification in real time.

Support Vector Machines is a fast classification method originally designed for binary classification.

Methods for multiclass classification based on support vector machines were constructed as multiclass classifiers which combine several binary classifiers. Comparison of multiclass SVM methods are detailed explained in [17], [35] so in this work, we will focus on best solution for our problem.

In order to achieve better classification results, in this chapter we propose and present a method that combines fuzzy logic and support vector machine method for data classification.This method is proposed for multiclass classification.As the SVM method is very fast and accurate when dealing with only two classes of data, fuzzy logic for classification was introduced as primary classifier choice and SVM method was used only for special cases when classified input data can belong to any of the class.

In fuzzification process learning examples are coding into fuzzy sets with memberships. This process is done during supervised learning. If C_i are categories where $i=1...n$and n is a number of categories, v_j represent training data where j is a number of templates. Each templatev_j can be observed as a set of pixels with specific color model values. For each category classifier, we use *Cb-Cr* pixel relation from YCbCr color model and, based on occurrence frequency, membership for each pixel relationμ is created.

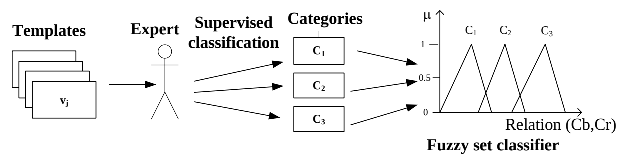

Fig.13 Fuzzy-SVM fuzzification

In defuzzification process, each pixel t is analyzed and membership to fuzzy set is determined for each class $\mu_{Ci}(t)$, $i=1\ldots n$ where n is number of classes.

By applying fuzzy logic, input data can have membership in several different classes with different degree of membership. To avoid misclassification problem threshold δ is introduced. Absolute difference between maximal membership value and second one compares with threshold. If the result is less than threshold, binary SVM method is applied between first two classes with maximum fuzzy membership value.

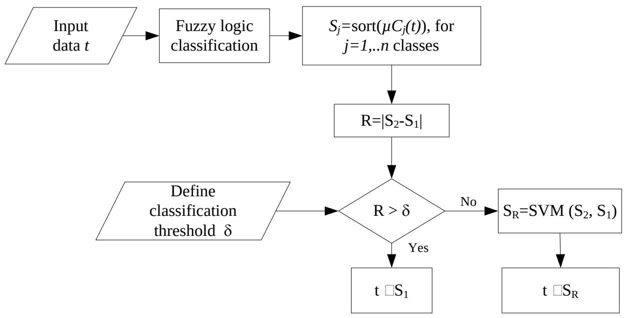

Fig.14 Fuzzy-SVM defuzzification

2.4 Classification methods evaluation

To evaluate quality of classifier's solutions, classification accuracy and confusion matrix are used [34]. Classification problem solutions success is measured with classification accuracy. This value is defined as a relative frequency of correct classifications:

$$Acc = \frac{n_{corr}}{n} \cdot 100\% \qquad (1)$$

Where n is the number of all possible examples for a given problem and n_{corr} the number of correctly classified examples by the current theory. The classification accuracy is a probability that a randomly selected example will be correctly classified. This value is an average over all classes and therefore does not tell anything about distribution of correct classifications, so for each class classification accuracy, confusion matrix is applied.

Table 5 Confusion matrix

Correct class	Classified as			Total
	A	B	C	
A	n(A,A)	n(B,A)	n(C,A)	n(A)
B	n(A,B)	n(B,B)	n(C,B)	n(B)
C	n(A,C)	n(B,C)	n(C,C)	n(C)
Total	n(A)'	n(B)'	n(C)'	|E|

Diagonal elements of the inner 3x3 table are values of correct classification (in percentages). The sum of each row is a prior probability of the respective class and the sum of each column is the percentage of all examples that were classified in the respective class.

Accuracy of tested method can be defined as:

$$A_{cc} = \frac{n(A,A)+n(B,B)+n(C,C)}{|E|} \cdot 100\%$$

3 Experiment and results

In order to test Fuzzy-SVM approach, domain expert extracted a set of pixels for each category defined in section 2. Foreach category, swimming pool, caps, body and splashing, fuzzy sets are created based on the data from the category templates (Fig.15).

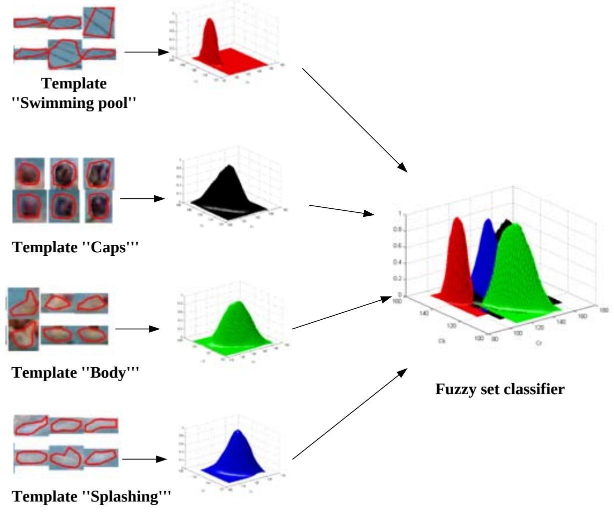

Fig.15Fuzzy set classifier

This process is a fuzzification process which is done with templates extracted with LabelMe annotation tool. After the fuzzy set classifier is created, it can be reused or updated for better classification.
The algorithm was implemented in Matlab 7 on Pentium dual-core 3.2MHz with 4 GB of RAM.
Proposed Fuzzy-SVM method was compared with the results obtained by four standard classification methods: multi-Support Vector Machines (m-SVM)[16], one-against-one SVM, nearest neighborhood (k-NN) with k=2[34] and Fuzzy logic classification[14].

Table 6 Classification of "swimming pool" pixels

	M-SVM	Fuzzy	k-NN	SVM-1A1	Fuzzy-SVM
Swimming pool	**90,0%**	**100%**	**99,5%**	**99,5%**	**100%**
Caps	0,0%	0,0%	0,0%	0,0%	0,0%
Splashing	0,0%	0,0%	0,5%	0,5%	0,0%
Player body	10,0%	0,0%	0,0%	0%	0,0%

Table 7 Classification of "caps" pixels

	M-SVM	Fuzzy	k-NN	SVM-1A1	Fuzzy-SVM
Swimming pool	1,0%	2,0%	1,0%	1,0%	2,0%
Caps	**72,5%**	**66,0%**	**86,0%**	**76,5%**	**77,5%**
Splashing	24,0%	9,5%	8,0%	7,5%	8,0%
Player body	2,5%	22,5%	5,0%	15,0%	12,5%

Table 8 Classification of "splashing" pixels

	M-SVM	Fuzzy	k-NN	SVM-1A1	Fuzzy-SVM
Swimming pool	3,0%	1,0%	0,0%	0,0%	1,0%
Caps	0,0%	5,5%	14,5%	10,5%	10,0%
Splashing	**97,0%**	**87,0%**	**83,0%**	**77,5%**	**87,5%**
Player body	0,0%	6,5%	2,5%	12,0%	1,5%

Table 9 Classification of "player body" pixels

	M-SVM	Fuzzy	k-NN	SVM-1A1	Fuzzy-SVM
Swimming pool	0,5%	0,5%	0,0%	0,0%	0,5%
Caps	44,5%	1,0%	10,0%	3,5%	3,5%
Splashing	3,5%	0,0%	0,5%	0,5%	0,0%
Player body	**51,5%**	**98,5%**	**89,5%**	**96,0%**	**96,0%**

Classification results for each category are shown in tables 6-9. From Table 6it is obvious that all classification methods show good recognition of pixels that belong to "swimming pool" category. This information is important because it can be used for implementation of this method in drowning detection systems or some other system that detect objects in swimming pool. For such systems, results presented inTable 9are also important. All methodsshow that player body can be well-recognized using proposed *Cb-Cr* method in swimming pool. Splashing pixels have also good results. As expected, classification of caps pixels showed the worst results, but proposed Fuzzy-SVM method shows better results than SVM methods and Fuzzy classification method. As previously pointed, caps have lots of noise and it is very hard to extract them correctly.

Table 10 Confusion matrix for multi-SVM method

Correct class	Classified as			
	Swimming pool	Caps	Splashing	Player body
Swimming pool	**90,0%**	0,0%	0,0%	10,0%
Caps	1,0%	**72,5%**	24,0%	2,5%
Splashing	3,0%	0,0%	**97,0%**	0,0%
Player body	0,5%	44,5%	3,5%	**51,5%**

Table 11 Confusion matrix for Fuzzy logic method

Correct class	Classified as			
	Swimming pool	Caps	Splashing	Player body
Swimming pool	**100,0%**	0,0%	0,0%	0,0%
Caps	2,0%	**66,0%**	9,5%	22,5%
Splashing	1,0%	5,5%	**87,0%**	6,5%
Player body	0,5%	1,0%	0,0%	**98,5%**

Table 12 Confusion matrix for nearest neighborhood method

Correct class	Classified as			
	Swimming pool	Caps	Splashing	Player body
Swimming pool	**99,5%**	0,0%	0,5%	0,0%
Caps	1,0%	**86,0%**	8,0%	5,0%
Splashing	0,0%	14,5%	**83,0%**	2,5%
Player body	0,0%	10,0%	0,5%	**89,5%**

Table 13 Confusion matrix for SVM-1A1 method

Correct class	Classified as			
	Swimming pool	Caps	Splashing	Player body
Swimming pool	**99,5%**	0,0%	0,5%	0,0%
Caps	1,0%	**76,5%**	7,5%	15,0%
Splashing	0,0%	10,5%	**77,5%**	12,0%
Player body	0,0%	3,5%	0,5%	**96,0%**

Table 14 Confusion matrix for Fuzzy-SVM method

Correct class	Classified as			
	Swimming pool	Caps	Splashing	Player body
Swimming pool	**100,0%**	0,0%	0,0%	0,0%
Caps	2,0%	**77,5%**	8,0%	12,5%
Splashing	1,0%	10,0%	**87,5%**	1,5%
Player body	0,5%	3,5%	0,0%	**96,0%**

Table 15 Classification evaluation results

M-SVM	**Fuzzy**	**k-NN**	**SVM-1A1**	**Fuzzy-SVM**
77,75%	87,88%	89,50%	87,38%	90,25%

Confusion matrix for each method is presented in tables 10-14 and in the Table 15are classification evaluation results. Results in Table 15 are obtained by classification evaluation method presented in section 2.4.From the evaluation results it is obvious that presented Fuzzy-SVM method is better than standard classification methods in combination with Cb-Cr pixel classification for detecting swimmers in water polo.

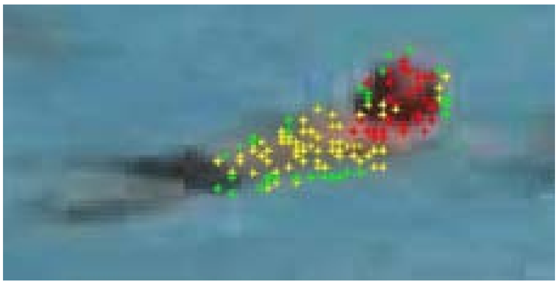

Fig.16 Method implementation on water polo player

For the experiment, we implemented proposed method and sampled 400 particles on water polo player. We used only data for caps, splashing and player body as we know that all around is swimming pool. One of the results obtained during player tracking sequence is shown inFig.16. Red dots are recognized as caps, yellow as body and green as splashing.

4 Conclusion

To the best of our knowledge, there are no domain-specific methods for objects classification objects and tracking players in water polo. In our work we focus on two things: selecting right features for tracking players in water polo and selecting the best classification method for category classification.

In the first part of our work, we focused on different color models based on previous scientific articles. Our theory was that relation Cb-Cr from YCbCr color model can provide the best results for features extracting in water polo and swimming pool swimmers generally.

In the second part of our work, we proposedtheFuzzy-SVM classification method based on pixel classification. This method combines the strength of Fuzzy logic and speed of SVM classification. Proposed classification method is tested on Cb and Cr relation for swimming pool, player caps, player body and splashing and compared with standard multiclass SVM and Fuzzy logic classification method.

Our experiment shows that classification in YCbCr domain with Cb and Cr in combination with proposed Fuzzy-SVM classifier has superior results for observed application domain. Furthermore, our preliminary method implementation on water polo player gives us encouraging results.

Further research will be focused in two directions: first, improvement of classification methods and second, implementing proposed method with particle filter tracking for tracking water polo players.

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