International Journal Of Engineering Research And Development
e-ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 14, Issue 3 (March Ver. II 2018), PP.37-44

An Hybrid Approach of LBP and Hu Moment Invariant Features For Fish Species Classification

Puneeth Kumar B S [1], Suresha M[2]
[1]*Department of Computer Science, Research Scholar, Kuvempu University, Karnataka, India.*
[2] *Department of Computer Science, Assistant Professor, Kuvempu University, Karnataka, India.*
Corresponding Author: Puneeth Kumar B S

ABSTRACT:- Computer vision is an advanced inspection innovation that has been applied in different fields. However, it isn't as generally utilized as a part of aquaculture. It is very challenging in underwater video to identify the fish species; the inspected fishes are sensitive, easily stressed and permitted to move in environment in which lighting, perceivability are the most part is not controllable. The proposed framework is to classify the fish species from videos captured by underwater cameras. First, extracted the foreground fish by background subtraction Model. Then, a Local Binary Pattern (LBP) technique used to get the texture of a fish. Then, for the fish texture, applied the method of Moment-Invariants (MI) coupled with geometrical concern and used to be accordingly invariant to scale of a fish, two dimensional fish orientation and location in the view of camera. A fusion of these two techniques overcome the LBP's variance to scale, rotation, translation by applying MI on LBP texture of fishes. Here, considered both the texture and geometrical features of fishes to classify fish species. Finally, a multi-class Support Vector machine(MSVM) classifier is applied to fish species classification. Experiment is conducted on publicly available Fish4Knowledge underwater video dataset and achieved the accuracy rate of 91.45%.

KEYWORDS:- LBP, Hu Moment Invariant Features, Multi-class SVM, Hybrid Features, Fish Classification.

Date of Submission: 12 -03-2018 Date of acceptance: 27-03 2018

I. INTRODUCTION

The fisheries and fish cultivating businesses today work in substantial and worldwide market [1].In such a worldwide and aggressive commercial centre, it is essential for the fisheries and fish cultivating ventures to investigate innovative answers for enhancing efficiency and benefit. In this context, uses of imaging advances are assuming an essential part in a few noteworthy regions in research and industry, including process optimization, computerized sorting and grading. Manual fish sorting by species is taken over on all business and research angling vessels [2]. This process is slow, labour dependent and has limits in terms of efficiency. At present all fish sorting by species is doing manually only after caught of fishes and weight by EC regulations [3].There is a requirement for an automated fish sorting system capable of recording fish species, trace and count fishes in accordance with species and catch the fish based on species.

Some scientist have proposed strategies for fish classification utilizing machine vision. Storbeck and Daan (2001)[4]proposed a fish species identification system by computer vision and a neural network program. The system measures a number of fish features like width and height by putting a fish on conveyor belt directly beneath the camera at various locations along the fish. White et al. (2006)[5] proposed a trails of computer vision machine (The Catch Meter) for identifying and measuring distinctive species in which the fish are transported along a conveyor belt underneath a digital camera by using of moment-invariant method and did the experiment on seven different fish species. These methods propose the fish species identification is offshore of sea on conveyor belt, which cannot meet the underwater video environment where the fishes have free movement and allowed to move in environment in which lighting, perceivability are for the most part not controllable.

Color and texture are basic features especially in color textured images [6]. Color is one of the most critical low-level feature that can be utilized to separate homogeneous areas of objects or part of objects [7].Texture can be defined as a local statistical pattern of texture primitives in an observer's view [8].Texture analysis plays an important role in image classification. Many researchers have proposed algorithms for texture analysis[9].

Tayama et al. (1982)[10] describe a technique for sorting fish varieties considering of shape and accomplished an sorting dependability of 95% for four types of fish. Wagner et al. (1987)[11] describe a similar sorting method for nine species of fish. Strachan, 1993a[12] uses colour and shape features for 23 species of fish to sort by species, with a sorting accuracy of 99% have been achieved . However, these results are obtained by using 50 samples of each species of fish. In this method, constructed a grid for round shaped fish and flat shaped fish which descript the shape as 36 elements. This works well for round shaped fish not for flat shaped fish, because flat shaped fish have the large aspect ratio, for which there is possibility of crossover of grid width lines. Again Strachan (1993a)[12] proposed a simple grid for shape whereby width lines are parallel to each other to avoid crossover grid width lines. This work needs that flat shaped fish must be fed through the system with a certain orientation. It leads in complexity. Arnarson and Pau, (1994); Strachan, (1993b)([13][14]) describes the vision system to measure the length of fish with less than 1cm error.

Our objective is to use the well-known texture and shape features for classification of fish species by hybridization of features and because of the MI region based shape descriptor make the LBP texture feature descriptor invariant to rotation, scaling and translation. The novel proposed method is the hybridization of LBP texture and Hu Moment Invariant. A motivation is that methods based on LBP texture and MI provide complementary information. LBP captures small and fine details whereas MI provides region based shape features over a broader range of scales with the contour based shape features and obtain the hybridized features and fed these features to multi-class Support Vector Machine(MSVM) for best possible classification of fish species.

II. DATA SET

We perform our experiment on video dataset created by Fish4Knowledge project [15],There are two types of video dataset All Years dataset and full day dataset ,which is about 200 Tb in size. All years dataset consists of video from all cameras at the 3 sites, for the time period 8:00-8:10.Total 5824 video files each of 25 Mb long (Oct 1, 2010 - July 10, 2013 - 1035 days captured by 9 cameras).Full Day dataset consists of videos from all cameras at the 3 sites, for all time periods (6:00 - 19:00, the daylight hours),here there are 690 videos (out of 702 cameras * 13 hours * 610 minute clips).We found 8 species of fish in the video which are considered for our experiment based on the prior knowledge about the fish species labelled manually by marine biologist [16]in which sample fish images are shown in Fig 1.

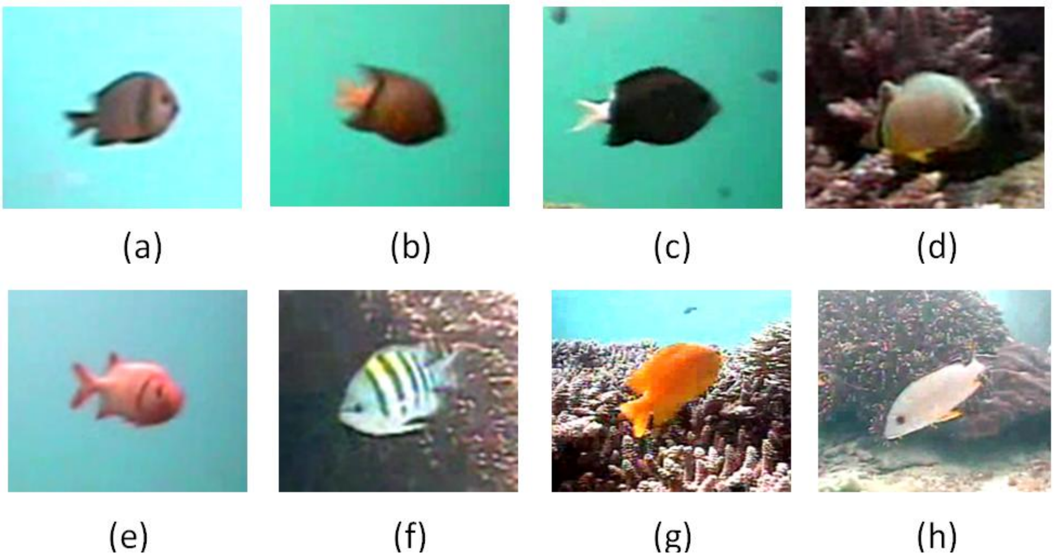

Fig 1:.Sample video frames from All Years dataset and Full Day dataset of Fish4Knowledge dataset.(a) Dascyllus reticulatus ,(b)Plectroglyphidodon dickii,(c)Chromis chrysura, (d)Chaetodon lunulatus,(e)Myripristis kuntee ,(f)Abudefduf vaigiensis ,(g)Pomacentrus moluccensis ,(h)Lutjanus fulvus.

Fishes are segmented from video with vary not only in orientation, position and size inside each class, but also in texture and colours.

III. PROPOSED METHODOLOGY

Proposed methodology consist of a novel approach for fish species identification by hybridizing the two well-known feature descriptors LBP texture feature descriptor and Hu Moment Invariant Shape descriptor, we obtain new Moment invariant shape features of fish LBP texture is fed in to Multi-class Support Vector machine(MSVM) for species classification. Before that to detect and extract the region of interest that is fish objects from video sequence we employ the Background modelling and subtraction technique, here background model is constructed using XCS-LBP descriptor. The Process of segmentation and classification shown in the

Fig 2.

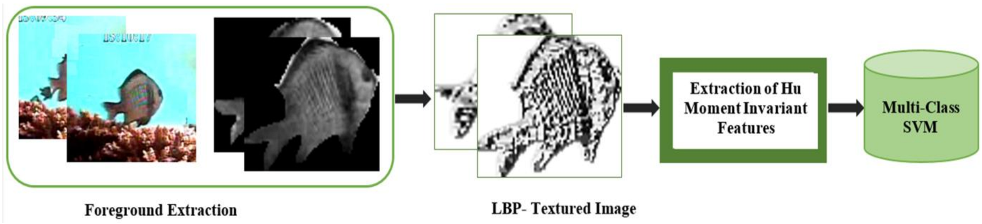

Fig 1: Fish Classification Model

A. XCS-LBP based Background Modelling and subtraction for motion fish segmentation

The LBP descriptor introduced by Ojala et al. [17] used to extract texture features it is simple and fast to compute. To address the above challenge, Heikila et al. [18] introduced the Centre Symmetric Local Binary Pattern modified LBP(CS-LBP).Silva et al.[19] proposed eXtended Centre Symmetric Local Binary Patterns(XCS-LBP]descriptor for background modelling and foreground extraction in videos an extension of CS-LBP is the one adapted in this paper to segment the motion of fishes. It compares the pairs of centre symmetric pixels and considers the centre pixel too. This technique gives shorter histograms and is ignores the sudden change in illumination conditions. The thought behind this implied for background subtraction utilized for both current frame and the background frame.

The XCS-LBP defined as below:

$$XCS-LBP_{P,R}(c)=\sum_{i=0}^{(P/2)-1} s(g_1(i,c)+g_2(i,c))2^i \qquad (1)$$

Where s is the threshold function used to determine types of local pattern transition, expressed as

$$s(x_1+x_2)=\begin{cases}1 & if\ (x_1+x_2)\geq 0\\ 0 & otherwise\end{cases} \qquad (2)$$

Where $g_1(i,c)$ and g2 (i,c) defined as:

$$g_1(i,c)=(g_i-g_{i+(P/2)})+g_c \qquad (3)$$

$$g_2(i,c)=(g_i-g_c)(g_{i+(P/2)}-g_c) \qquad (4)$$

Where g_c is the gray value of the centre pixel c and g_i and $g_{i+(P/2)}$ are the gray values ofsymmetric pairs of pixels. Unlike CS-LBP it is worth because no need of user-defined threshold value.

The computation of the XCS-LBP is shown in Fig 3.

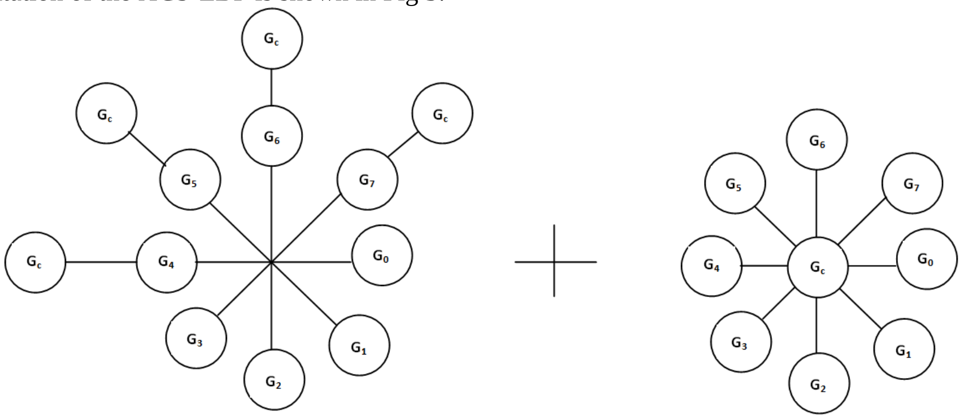

Fig 3: The XCS-LBP descriptor

The binary pattern of XCS-LBP given below

$$XCS-LBP = \begin{cases} S((g_0 - g_4) + g_c + (g_0 - g_c)(g_4 - g_c))2^0 + \\ S((g_1 - g_5) + g_c + (g_1 - g_c)(g_5 - g_c))2^1 + \\ S((g_2 - g_6) + g_c + (g_2 - g_c)(g_6 - g_c))2^2 + \\ S((g_3 - g_7) + g_c + (g_3 - g_c)(g_7 - g_c))2^3 \end{cases} \quad (5)$$

The XCS-LBP produces a shorter histogram than LBP and ignores the small changes in illumination. XCS-LBP is more efficient for background modelling and subtraction.
The moving fishes have been identified after background subtraction. Then we apply open morphological operation is used to merge the small separated features and Flood fill morphological operation to fill holes, if there is any.

B. LBP Texture image

Title The LBP operator is basically designed for describe the texture was introduced by Oajala et al., [20].The generic LBP is derived as below based on [21, 22,17].
Consider a monochrome image *I(x,y)* and let g_c denote the gray level of an arbitrary pixel *(x,y)*, i.e. *gc = I(x,y)*. Let g_p denote the gray value of a evenly spaced circular neighbourhood sampling point of *P* sampling points and radius *R* around point *(x,y)*:

$$g_p = I(x_p, y_p), \quad p = 0,1,2,......., P-1 \text{ and} \quad (6)$$

$$x_p = x + R\cos(2\pi p / P), \quad (7)$$

$$y_p = y - R\sin(2\pi p / P). \quad (8)$$

Assuming that the local texture of an image *I(x,y)* is characterized by the joint distribution of gray values of *P* + 1 *(P* >0*)* pixels:

$$T = t(g_c, g_0, g_1,........, g_{p-1}). \quad (9)$$

Without loss of information, the centre pixel value can be subtracted from the neighbourhood pixels:

$$T = t(g_c, g_o - g_c, g_1 - g_c,....., g_{p-1} - g_c). \quad (10)$$

In the next step the joint distribution is approximated which allows for factorization of distribution by assuming the centre pixel to be statistically independent of the differences.

$$T \approx t(g_c)t(g_0 - g_c, g_1 - g_c,...., g_{P-1} - g_c). \quad (11)$$

Now the first factor *t(g$_c$)* is the intensity distribution over *I(x,y)*. From the point of view of analysing local textural patterns, instead the joint distribution of differences, it contains no useful information.

Signs of the difference considered as below:

$$t(s(g_0 - g_c), s(g_1 - g_c),......., s(g_{P-1} - g_c)), \quad (12)$$

where *s(z)* is the thresholding (step) function

$$s(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0. \end{cases} \quad (13)$$

The generic local binary pattern operator derived from this joint distribution. As in the case of basic LBP, it obtained by summing the thresholder differences weighted by powers of two. The LBP$_{P,R}$ operator defined as

$$LBP_{P,R}(x_C, y_C) = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \quad (14)$$

According to Equation (14) the signs of the differences in a neighbourhood are interpreted as a *P*-bit binary number, leading to 2^Pdistinct values for the LBP code. The local gray-scale distribution, i.e. texture T can be approximately represented with a 2^P-bin discrete distribution of LBP codes:

$$T \approx t(LBP_{P,R}(x_c, y_c)). \quad (15)$$

When P=8 and R=1, LBP$_{8,1}$, which is the basic LBP descriptor, can be obtained. The LBP$_{8,1}$ operator derives an 8-bit binary code by comparing the centre pixel to each of its eight nearest neighbour in a 3X3 neighbourhood. The resulting 8 bits circularly concatenated to form an LBP code within the range of [0, 255]. In this manner, a

256-bin histogram created to obtain the occurrences of different binary patterns over an image. The basic LBP is shown in Fig 4.

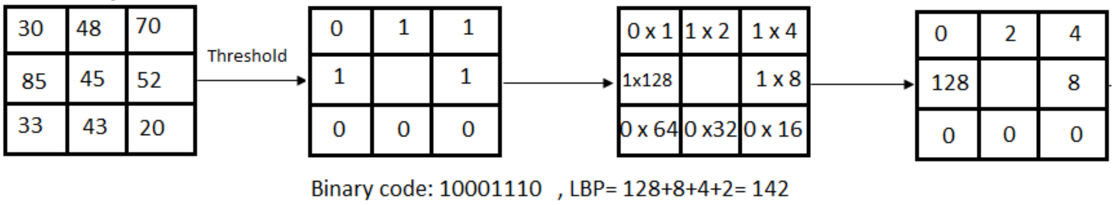

Fig 4: Basic LBP Operator

C. Hu Moment Invariant for LBP Textured Fish image

An effective shape description constitutes a key part in the classification process for this purpose, a favourable shape descriptor should have high variability in order that it can group similar shapes together and separate dissimilar shapes into different groups. It is also expected that a stable shape descriptor should be invariant to common geometrical transformations and robust to shape boundary distortion. Throughout the past decades, various form of shape descriptors has been proposed in the context of content-based image retrieval and pattern recognition systems. According to [23, 24, 26], these can be broadly categorized into two groups, namely, contour- and region-based descriptors. Contour-based shape descriptors such as Fourier descriptors [25], ignore potentially important information in the shape interior. Consequently, they are sensitive to variations of object boundaries and can't manage with disjoint shapes where contour information may not be available. Compared with contour-based ones, region-based methods are more appropriate for general applications [26]. Indeed, region-based shape descriptors accomplish information from both boundaries and interior regions of the shape. Among them, the best-known ones are moments-based descriptors which have been extremely mainstream since they were first introduced in the 60's [27]. These include the Hu moments Invariant descriptor beats the other moments descriptors in terms of invariance, computation complexity, robustness to noise and distortions.

The image moment is a particular average of intensities of all pixels. In common, there are four generation of image moments.

The first generation is the "raw moment". For a 2D image $I(x, y)$, the raw moment A of order (u, v) is defined as

$$A_{(u,v)} = \sum_x \sum_y x^u y^v I(x,y) \tag{16}$$

where $u, v = 0, 1, 2….$

The second generation is the "central moment", which adds translation invariant on raw moment [28]. The central moment B of order (u, v) is defined as:

$$B_{(u,v)} = \sum_x \sum_y (x - E(x))^u (y - E(y))^v I(x,y) \tag{17}$$

The E(x) and E(y) are defined as

$$E(x) = \frac{A_{(1,0)}}{A_{(0,0)}} \tag{18}$$

$$E(y) = \frac{A_{(0,1)}}{A_{(0,0)}} \tag{19}$$

The third generation is called as "normalized central moment", which adds scale invariant on the central moment [29]. The normalized central moment C of order (u, v) is defined as

$$C_{(u,v)} = \frac{B_{(u,v)}}{\left(B_{(0,0)}\right)^{(\frac{u+v}{2}+1)}} \tag{20}$$

The fourth generation is called "Hu moment" [30]. It adds rotation invariant based on normalized central moment. Seven Hu moment invariants [$D1$, $D2$, $D3$, $D4$, $D5$, $D6$, $D7$] are expressed below:

$$D_1 = C_{(2,0)} + C_{(0,2)} \tag{21}$$

$$D_2 = (C_{(2,0)} - C_{(0,2)})^2 + 4C_{(1,1)}^2 \tag{22}$$

$$D_3 = (C_{(3,0)} - 3C_{(1,2)})^2 + (3C_{(1,2)} - C_{(0,3)})^2 \tag{23}$$

$$D_4 = \left(C_{(3,0)} + C_{(1,2)}\right)^2 + (C_{(2,1)} + C_{(0,3)})^2 \tag{24}$$

$$\begin{aligned} D_5 &= (C_{(3,0)} + C_{(1,2)})^2 + (C_{(2,1)} + C_{(0,3)})^2 \left[\left(C_{(3,0)} + C_{(1,2)}\right)^2 - 3\left(C_{(2,1)} + C_{(0,3)}\right)^2\right] + \\ &\left(3C_{(2,1)} - C_{(0,3)}\right)\left(C_{21} + C_{03}\right)\left[3(C_{(3,0)} + C_{(1,2)})^2 - (C_{(2,1)} + C_{(0,3)})^2\right] \end{aligned} \tag{25}$$

$$\begin{aligned} D_6 &= \left(C_{(3,0)} - C_{(0,2)}\right)\left[\left(C_{(3,0)} + C_{(1,2)}\right)^2 - \left(C_{(1,2)} + C_{(0,3)}\right)^2\right] \\ &+ 4C_{(1,1)}(C_{(3,0)} + C_{(1,2)})\left(C_{(2,1)} + C_{(0,3)}\right) \end{aligned} \tag{26}$$

$$\begin{aligned} D_7 &= (3C_{(2,1)} - C_{(0,3)})\left(C_{(3,0)} + C_{(1,2)}\right)\left[\left(C_{(3,0)} + C_{(1,2)}\right)^2 - 3\left(C_{(2,1)} + C_{(0,3)}\right)^2\right] \\ &- \left(C_{(3,0)} - 3C_{(1,2)}\right)\left(C_{(2,1)} + C_{(0,3)}\right)\left[3(C_{(3,0)} + C_{(1,2)})^2 - (C_{(2,1)} + C_{(0,3)})^2\right] \end{aligned} \tag{27}$$

In all, the Hu moment invariant (HMI) are translation, scale, and rotation invariants and has been successfully applied in scattered object recognition, object detection, vision tracking, shape measure, etc. In this study, we chose the seven HMIs of [*D*1, *D*2, *D*3, *D*4, *D*5, *D*6, *D*7] as the global features of LBP textured fish images.

IV. RESULTS AND DISCUSSION

In this section, supervised classification method used to improve the accuracy of classifier. In supervised classification technique, at first classifier trained with the training data set and later accuracy of classifier is trailed utilising testing set. Training set incorporates labelled data set, which can train the classifier to accurately classify the classes of testing samples. Based on the trails performed, it was analysed that multi-class support vector machine (MSVM) classifier provides highest accuracy to classify Fish4Knowledge data set.

The eight species and the number of each species found in a video that we consider for experiment is shown in table 1.

Table I: Eight fish species and their numbers of count found in video consider for experiment

Name of the fish Species	Number of images
Dascyllus reticulatus	120
Plectroglyphidodon dickii	68
Chromis chrysura	70
Chaetodon lunulatus	50
Myripristis kuntee	44
Abudefduf vaigiensis	60
Pomacentrus moluccensi	65
Lutjanus fulvus	63

Since it was impossible to use one of the sets of fish images to train the algorithm and test it with the other set, a 4-fold cross validation test carried out with each of the sets in order to evaluate the performance of this method. The test procedure worked as follows.

1. Randomly split the dataset into four subsets.
2. Three of the subsets used as a Training set.
3. The remaining one sub-set was used as a testing set
4. Each of four possible pairs of training and testing sets were trained (for selection of threshold values) and tested.
5. The performance of the method determined by the accuracy of average test-set classification.

Table 1 provide the experimental results in the form of confusion matrix. The highest rate with respect to each species is emboldened. The average accuracy of all fish species is 91.45%. The species Dascyllusreticulates, *Plectroglyphidodondickii and Chromischrysura* are yielding less accuracy when compared with five species this is because of light source is behind the fish objects and this makes LBP with the poor texture, and all the above-mentioned fish species are more similar accordance with a fish shape. In this circumstance classification is mainly depends only on shape of a fish, because of shape has a more variance than texture in this particular circumstance

Table II. Confusion matrix which includes classification rates reached by proposed method using Multi-class Support Vector machine(MSVM).

Presented	**Responded**							
	Dascyllus reticulatus	*Plectroglyphido -don dickii*	*Chromis chrysura*	*Chaetodon lunulatus*	*Myripristis kuntee*	*Abudefduf vaigiensis*	*Pomacentrs moluccensi*	Lutjanus Fulvus
Dascyllus reticulates	**86.8**	4.4	6.8	-	-	-	2.0	-
Plectroglyphidodon dickii	6.8	**87.8**	5.4	-	-	-	-	-
Chromis chrysura	5.1	4.8	**87.9**	-	-	-	-	2.2
Chaetodon lunulatus	3.1	2.3	-	**88.3**	-	-	-	6.3
Myripristis kuntee	2.6	2.3	-	-	**92.8**	-	2.3	-
Abudefduf vaigiensis	-	-	-	-	-	**100**	-	-
Pomacentrus moluccensi	-	3.5	-	-	3.1	-	**93.4**	-
Lutjanus fulvus	-	-	-	2.8	2.6	-	-	**94.6**

V. Conclusion

A novel hybrid LBP and Hu Moment Invariant fusion method proposed for fish classification. Segmented fishes in an underwater video by background subtraction model using XCS-LBP, which is well known for eliminating an illumination with the complex video sequences like underwater videos. LBP is used for texture extraction of fish and the Hu Moment Invariant descriptor is used for contour and region based shape features of fishes this helps in the analysis of fish texture by the means of shape, yields a good performance of average 91.45% accuracy. Conducted classification using Multi-class support Vector Machine which gives the highest accuracy as per the survey we have done on the Fish4Knowledge dataset.

REFERENCES

[1]. European Commission (2009) "A sustainable future for transport: Towards an integrated, technology-led and user friendly system", EU COM (2009) 279 final, Luxembourg.

[2]. Strachan, N.J.C., 1994. Sea trials of a computer vision-based fish species sorting and size grading machine. Mechatronics 4 (8), 773–783.

[3]. EC, 1986. Commission Regulation 3703/85, Common Fisheries Policy, Community Grading Rules. A guidance note for the fishing industry. Issued by the UK Fisheries Departments.

[4]. Storbeck, F., Daan, B., 2001. Fish species recognition using computer vision and a neural network. Fisheries Research 51 (1), 11–15.

[5]. White, D.J., Svellingen, C., Strachan, N.J.C., 2006. Automated measurement of species and length of fish by computer vision. Fisheries Research 80 (2–3), 203– 210.

[6]. Kima, J.S., Hong, K.S., 2009. Color–texture segmentation using unsupervised graph cuts. Pattern Recognition 42 (5), 735–750.

[7]. Tan, K.S., Isa, N.A.M., 2011. Color image segmentation using histogram thresholding – Fuzzy C-means hybrid approach. Pattern Recognition 44 (1), 1–15.

[8]. Sengur, A., 2008. Wavelet transform and adaptive neuro-fuzzy inference system for color texture classification. Expert Systems with Applications 34 (3), 2120–2128.

[9]. Sengur, A., Turkoglu, I., Ince, M.C., 2007. Wavelet packet neural networks for texture classification. Expert System with Application 32 (2), 527–533.

[10]. Tayama, M., Shimadate, N., Kubota, N., Nomure, Y., 1982. Application for optical sensor to fish sorting. Reito (Tokyo). Refrigeration 57, 1146–1150.

[11]. Wagner, H., Schmidt, U., Rudek, J.H., 1987. Distinction between species of sea fish. Lebesmittelindustrie 34, 20–23.

[12]. Strachan, N.J.C., 1993a. Recognition of fish species by colour and shape. Image Vision Comput. 11 (1), 2–10.

[13]. Arnarson, H., Pau, L.F., 1994. Pdl-Hm – morphological and syntactic shape classification algorithm – real-time application to fish species classification. Mach. Vision Appl. 7 (2), 59–68.

[14]. Strachan, N.J.C., 1993b. Length measurement of fish by computer vision. Comput. Electron. Agric. 8, 93–104.

[15]. P.X. Huang, B.J. Boom, R.B. Fisher, Underwater live fish recognition using a balance-guaranteed optimized tree, in: Computer Vision–ACCV 2012, Springer, Daejeon, Korea, 2013, pp. 422–433.

[16]. B. J. Boom, P. X. Huang, J. He, R. B. Fisher, "Supporting Ground-Truth annotation of image datasets using clustering", 21st Int. Conf. on Pattern Recognition (ICPR), 2012.

[17]. Ojala T, Pietikäinen M, Mäenpää T (2002) Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans Pattern Anal Mach Intell 24(7):971–987.

[18]. Heikkilä M, Pietikäinen M, Schmid C (2009) Description of interest regions with local binary patterns. Pattern Recogn 42:425–436.

[19]. Silva C, Bouwmans T, Frélicot C (2015) An eXtended center-symmetric local binary pattern for background modelling and subtraction in videos. MIA - Mathématiques, image et applications, international joint conference on computer vision, imaging and computer graphics theory and applications, VISAPP 2015,Mar 2015, Berlin, Germany

[20]. T. Ojala, M. Pietikainen, and D. Harwood, “A comparative study of texture measures with classification based on feature distributions,” Pattern Recognition, vol. 29, no.1, pp. 51–59, January 1996.

[21]. Mäenpää, T.: The local binary pattern approach to texture analysis—extensions and applications. PhD thesis, Acta Universitatis Ouluensis C 187, University of Oulu (2003).

[22]. Mäenpää, T., Pietikäinen, M.: Texture analysis with local binary patterns. In: Chen, C.H., Wang, P.S.P. (eds.) Handbook of Pattern Recognition and Computer Vision, 3rd edn., pp. 197–216. World Scientific, Singapore (2005).

[23]. Celebi M. And Aslandogan Y.,”A Comparative Study of Three Moment-based Shape Descriptors,”in Proceedings of IEEE International Conference on Information technology: Coding and Computing, Las Vegas, vol. 1, pp 788-793,2005.

[24]. Loncaric S., “A Survey of Shape Analysis Techniques,” Pattern Recognition, vol. 31, no. 8, pp. 983-1001, 1998

[25]. Persoon E. and Fu K., “Shape Discrimination using Fourier Descriptors,” IEEE Transaction on Systems, Man, and Cybernetics, vol. 7, no.3,pp.170-179, 1977.

[26]. Zhang D. and Lu G., “Review of shape Representation and Description Techniques Pattern Recognition, vol. 37,no. 1, pp. 1-19. 2004.

[27]. Hu M., “Visual Pattern Recognition by Moment Invariants,” IRE Transaction on Information Theory, vol. 8, no. 2, pp. 179-187, 1962.

[28]. Wang YQ, Peng ZM. The optimal fractional S transform of seismic signal based on the normalized second-order central moment. J Appl Geophysics 2016;129:8–16.

[29]. Mise O, Bento S. Object detection and classification using image moment functions in the applied video and imagery analysis. In: Conference on Signal Processing, Sensor Fusion, and Target Recognition XXII. Baltimore, MD: Spie-Int Soc Optical Engineering; 2013.

[30]. Hu M-K. Visual pattern recognition by moment invariants. Inf Theory IRE Trans 1962;8(2):179–87.