ABNORMAL MOTION DETECTION IN VIDEO USING STATISTICS OF SPATIOTEMPORAL LOCAL KINEMATICS PATTERN

Jing Tian and Li Chen

†School of Computer Science and Technology, Wuhan University of Science and Technology
‡Hubei Province Key Laboratory of Intelligent Information Processing and Real-time Industrial System, Wuhan University of Science and Technology, Wuhan, China, 430081
Email: jingtian@ieee.org, chenli@ieee.org

ABSTRACT

Biomedical studies show that mutant genes in transgenic mutant fishes can lead to muscle disorders so that their swimming capabilities are affected. This paper studies the automatic detection of abnormal mutant fishes by analyzing their movements in the video. To differentiate between normal fish and mutant fish, a new feature extraction method, called *spatiotemporal local kinematics pattern* (STLKP), is proposed in this paper to provide discriminative spatiotemporal kinematics measurements of fish body movements. Furthermore, the histogram of the proposed STLKP features is incorporated into a motion classification approach to identify whether the fish is normal or a mutant. A large collection of real-world recorded videos is used in experiments to demonstrate that the proposed approach outperforms the conventional approaches to provide more accurate abnormal motion detection performance.

Index Terms— abnormal motion detection; motion classification; feature extraction;

1. INTRODUCTION

The mutant genes in transgenic mutant fishes could lead to muscle disorders and affecting their swimming capabilities, as proved in biomedical studies [1]. This has raised the requirement of the development of automatic computer vision approach, which can provide efficient and reliable analysis of fish movement in video data.

This paper studies the detection of abnormal mutant fishes in video by analyzing their movements. The motivation of this research is presented in many aspects [2]. First, in biomedical disease modeling applications, this study is potential to identifying which biomedical mutant model could lead to muscle disorders of fishes. Second, in drug development and screening applications, we can treat fishes using certain drugs. This study would be useful to evaluate whether the drugs are effective to recover the swimming capabilities of fishes or not. Third, in environmental monitoring applications, fishes tend to have abnormal movements due to low water quality. This study could be used to evaluate water quality.

Conventional studies of fish movements in video can be classified into the following two categories. First, the fishes are tracked to extract low-level motion features, such as distance traveled and velocity [3–5]. Second, the fishes are segmented into various body parts, so that fine kinematics can be measured, such as body elongation and angular velocity [6,7]. High frame-rate videos are used in [8, 9], where the fishes are automatically tracked using a pre-defined fish body contour model, and several motion features are extracted based on segmented fish body in the video. This also motivates this paper to use high frame-rate video to study fish movements and detect mutant fishes, since they usually have abnormal movements due to muscle disorders.

This paper proposes to automatically analyse the fish motion in video and identify if the fish is normal or a mutant. The proposed approach is motivated by the observation that mutant fishes have muscle disorders so that their bodies cannot bend sufficiently to swim normally. Thus, we analyze the kinematics features of fish movement in the video to develop an abnormal motion detection approach. The proposed approach first extracts kinematics features of fish in the video. Then the spatial and temporal features of the kinematics measurements are extracted to construct a new feature, called *spatiotemporal local kinematics pattern* (STLKP). The proposed STLKP feature is inspired by the conventional *local binary pattern* (LBP) operator [10]. However, the proposed STLKP feature is calculated using kinematics measurements, rather than intensity values used in the conventional LBP operator. Furthermore, the statistics of the proposed STLKP features are incorporated into the conventional *support vector machine* (SVM) classifier to detect abnormal fish motion in video.

The rest of this paper is organized as follows. The proposed STLKP feature extraction is described in Section 2, followed by a motion classification framework. Then, experiments are conducted in Section 3 to evaluate the performance

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of the proposed approach for identifying mutant fish. Finally, Section 4 concludes this paper.

2. PROPOSED APPROACH

The goal of of this study is to differentiate the normal fishes and mutant fishes via studying their motion in the recorded video. The proposed approach has the following three key components: (i) a kinematics feature extraction method is utilized to measure the kinematics of fish body movement in the video; (ii) a STLKP is proposed to extract spatial and temporal features of the kinematics measurements; (iii) a motion classification method is applied to provide a binary decision on whether the fish is normal or a mutant. The details of these three components are described in following subsections in details.

2.1. Kinematics feature extraction

The biomedical studies [1] show that the mutant fishes tend to yield lower body bending degree during the swimming, since their movements are affected by their muscle disorders. Inspired by this study, a kinematic feature, more specifically, the curvature of fish body bending, is used in this paper to provide kinematics measurements of fish movement as follows. First, we track the fish in the video, extract the skeleton of the tracked fish in each frame, and align the extracted skeletons according to the head-to-tail order. Then we uniformly sample along the body's curvature to obtain M control points. Then, we calculate the curvature measurement at each control point to botain K, where K is a $M \times 1$ vector with M being the number of measurements in each frame.

More specifically, the curvature measured at the i-th point of the t-th frame is defined as:

$$K(t,i) = \frac{(I_x^t + I_y^t)(I_{xx}^t I_x^t + I_{yy}^t I_y^t)}{\sqrt[3/2]{(I_x^t)^2 + (I_y^t)^2}} - \frac{I_{xx}^t + I_{yy}^t}{\sqrt{(I_x^t)^2 + (I_y^t)^2}}, \tag{1}$$

where four differential operators are $I_x^t = x^t(i+1) - x^t(i), I_y^t = y^t(i+1) - y^t(i), I_{xx}^t = x^t(i+1) - 2x^t(i) + x^t(i-1), I_{yy}^t = y^t(i+1) - 2y^t(i) + y^t(i-1)$, in which $x^t(i), y^t(i)$ are coordinates at the i-th point of the t-th frame.

2.2. Proposed spatiotemporal local kinematics pattern (STLKP)

After obtaining the kinematics measurements in the previous subsection, we calculate the STLKP at each control point of the fish body. Denote $K_{t,c}$ be the kinematic measurement at the location c of the t-th frame. The conventional LBP operator [10] can be used to describe the relationship between the center pixel and its surrounding neighbors by computing gray-level differences. By applying the LBP operator on the kinematics feature, the *local kinematics pattern* (LKP) can be obtained as

$$LKP_{P,R}(t,c) = \sum_{p=0}^{P-1} S(K(t,p) - K(t,c))2^p, \tag{2}$$

where P is the number of neighbors and R is the radius of the neighborhood, $K(t,c)$ and $K(t,p)$ are the kinematics values at the center location and its neighbor. The thresholding function $s(\cdot)$ is defined as

$$S(K(t,p) - K(t,c)) = \begin{cases} 1, & K(t,p) - K(t,c) \geq 0; \\ 0, & K(t,p) - K(t,c) < 0. \end{cases} \tag{3}$$

The LKP operator defined in (2) only deals with the spatial information of the kinematics measurements of fish movement. It is extended to a spatiotemporal representation for dynamic kinematics analysis. The idea behind is to consider dynamic kinematics as a set of volumes space. The neighborhood of each kinematics measurement is thus defined in three dimensional space. Then, similarly to LKP in spatial domain, a three dimensional neighborhood can be defined to extract its STLKP features and histogram as follows.

- Fist, a three dimensional spatiotemporal kinematics neighborhood is constructed as illustrated in Figure 1. Denote $K(t,c)$ as the kinematics measurement at the location c of the t-th frame. Its spatiotemporal neighboring measurements (denoted as Ω), which have the radius R_s and R_t defined in the spatial domain and the temporal domain, respectively, is defined as $\Omega = \{K(t - \lfloor R_t/2 \rfloor, c - \lfloor R_s/2 \rfloor), \ldots, K(t + \lfloor R_t/2 \rfloor, c + \lfloor R_s/2 \rfloor)\}$, and the total number of neighbors is $P = R_s * R_t$.

- Second, by applying the LKP operator (2) on the three dimensional spatiotemporal kinematics neighborhood, the proposed STLKP feature is deduced as

$$STLKP_{R_s,R_t,P}(t,c) = \sum_{p=0}^{P-1} S(K(t,p) - K(t,c))2^p, \tag{4}$$

  in which $K(t,p) \in \Omega$, the thresholding function $s(\cdot)$ is defined as (3).

- Finally, the histogram of the proposed STLKP feature for the t-frame is obtained as

$$H(t,i) = \sum_c I\{STLKP_{R_s,R_t,P}(t,c) = i\}, i = 0, 1, \ldots, 2^P - 1, \tag{5}$$

  where $H(t,i)$ is the i-bin of the histogram, $I(A) = 1$ if A is true; otherwise, $I(A) = 0$.

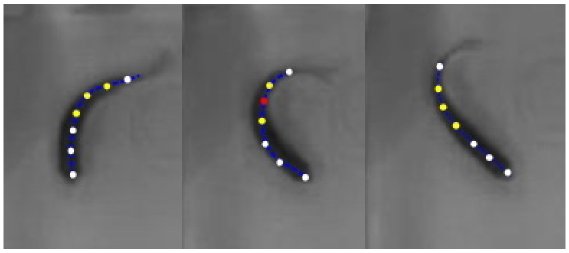

Fig. 1. An illustration of calculating the proposed STLKP feature using three frames of fish movement video. First, for each frame, fish body skeleton is extracted as blue dash line. For each blue dash line, the control points (marked as dots) are uniformly sampled along the fish body skeleton, then the kinematics measurements are calculated at each control point using (1). To calculate the proposed STLKP feature at the kinematic measurement $K(t, c)$ at the location c of the t-th frame (marked as red dot), a three dimensional spatiotemporal kinematics neighborhood is constrcuted based on radius values $R_s = 3$, $R_t = 3$ in spatial and temporal domains, respectively. That means, this neighborhood is a set of kinematics measurements consisting of yellow points $\Omega = \{K(t-1, c-1), K(t-1, c), K(t-1, c+1), K(t, c-1), K(t, c), K(t, c+1), K(t+1, c-1), K(t+1, c), K(t+1, c+1)\}$. Then, the proposed STLKP feature is calculated using (4).

2.3. Motion classification

The histogram of the proposed STLKP features defined in (5) can be calculated for each frame of the fish motion video, and the calculated histograms are concatenated together to form the discriminative feature for the fish motion video. It is further incorporated into a motion classification approach to provide binary decision on whether the studied fish is normal or a mutant. For that, a supervised learning approach is utilized in this paper to train a linear SVM classifier [11] based on the extracted histogram of STLKP features of fish motion video.

3. EXPERIMENTAL RESULTS

3.1. Video dataset

Experiments are conducted to evaluate the performance of the proposed approach and validate its capability to differentiate between normal and mutant fish movements. Two video datasets are used in our experiments. The first video dataset contains 240 video segments of 12 normal fishes and 12 mutant fishes, and the second dataset contains 200 video segments of 10 normal fishes and 10 mutant fishes. The videos are recorded at a frame rate of 250 frames per second, with a resolution of 480×640 pixels per frame.

3.2. Performance evaluation

The first experiment is to evaluate the proposed approach and compare it with other seven conventional abnormal fish motion detection approaches [3–9] The parameters of the proposed approach is set to be $M = 30$, $R_s = 5$, $R_t = 3$. The same parameters are used for all videos.

In our experiment, the aim is to differentiate mutant fish and normal fish. First, we calculate the following four performance measurements based on classification results: (i) *True positive* (TP): an identified mutant fish is really is a mutant; (ii) *True negative* (TN): an identified normal fish is really normal; (iii) *False negative* (FN): an identified normal fish is actually a mutant; and (iv) *False positive* (FP): an identified mutant fish is actually normal. After that, the performance of various approaches are evaluated in terms of five metrics: *Sensitivity*, *Specificity*, *Precision*, *Accuracy*, *F1 Score*. The sensitivity and specificity are statistical measures of how well the proposed approach identifies the mutant fish and normal fish, respectively. The precision and accuracy measures the ratios of positive correct detections and total correct detections, respectively. The F1 score is the harmonic mean between precision and recall. All of these are widely used in the performance evaluation of motion classification research [12]. The performance of various approaches is compared in Tables 1 and 1, where one can see that the proposed approach outperforms the conventional approaches to achieve the best classification performance with the highest values in these five performance evaluations.

4. CONCLUSIONS AND FUTURE WORKS

An abnormal motion detection approach has been proposed in this paper to analyze fish movements in video. The proposed STLKP features are exploited to represent the fish kinematics movements, and then further incorporated into a classification approach. The proposed approach is able to outperform conventional approaches to differentiate between the movements of normal fish and mutant fish, as verified in our experimental results. Therefore, the proposed approach can be used to validate the model that mutant genes in transgenic mutant fish lead to muscle disorders.

There are several issues need to be further studied for future research. First, the proposed approach is applicable on analyzing motion of single fish in the video only. It is interesting to further evaluate the performance of the proposed approach to study multiple fishes in the video. Second, the proposed approach only utilizes the curvature features of fish body movement to extract the proposed STLKP features. It would be interesting to evaluate other kinematic features.

Table 1. The abnormal motion detection performance (%) comparison of various approaches using the dataset 1. Larger value indicates better performance.

Performance	Ref. [8]	Ref. [3]	Ref. [6]	Ref. [7]	Ref. [4]	Ref. [5]	Ref. [9]	Proposed approach
Sensitivity	72.56	62.59	65.09	73.80	73.68	80.26	66.12	81.60
Specificity	81.86	72.10	77.30	72.13	79.44	81.35	82.99	87.87
Precision	70.08	67.96	65.09	64.58	72.59	64.89	76.63	81.60
Accuracy	78.43	67.48	72.49	72.81	76.99	81.02	75.27	85.38
F1 Score	71.30	65.16	65.09	68.88	73.13	71.76	70.99	81.60

Table 2. The abnormal motion detection performance (%) comparison of various approaches using the dataset 2. Larger value indicates better performance.

Performance	Ref. [8]	Ref. [3]	Ref. [6]	Ref. [7]	Ref. [4]	Ref. [5]	Ref. [9]	Proposed approach
Sensitivity	56.16	55.97	52.41	44.03	63.01	53.21	54.22	66.07
Specificity	91.47	85.08	88.54	89.01	86.92	87.93	92.21	92.76
Precision	73.87	66.96	68.42	61.53	73.01	62.36	79.38	82.22
Accuracy	80.86	74.86	76.94	76.17	78.32	78.44	78.69	83.78
F1 Score	63.81	60.97	59.36	51.33	67.64	57.42	64.43	73.26

5. REFERENCES

[1] W. Cheng, J. Tian, J.-M. Burgunder, W. Hunziker, and H.-L. Eng, "Myotonia congenita-associated mutations in chloride channel-1 affect zebrafish body wave swimming kinematics," *PLoS ONE*, vol. 9, no. 8, 2014.

[2] T. Liu, "A quantitative zebrafish phenotyping tool for developmental biology and disease modeling," *IEEE Signal Processing Magazine*, vol. 24, no. 1, pp. 126–129, Jan. 2007.

[3] C. Spampinato, S. Palazzo, B. Boom, J. Ossenbruggen, I. Kavasidis, R. D. Salvo, F.-P. Lin, D. Giordano, L. Hardman, and R. B Fisher, "Understanding fish behavior during typhoon events in real-life underwater environments," *Multimedia Tools and Applications*, vol. 70, no. 1, pp. 199–236, May 2014.

[4] C. Spampinato, D. Giordano, S. D. Salvo, Y.-H. J. Chen-Burger, R. B. Fisher, and G. Nadarajan, "Automatic fish classification for underwater species behavior understanding," in *Proc. ACM Int. Workshop on Analysis and Retrieval of Tracked Events and Motion in Imagery Streams*, Firenze, Italy, Oct. 2010, pp. 45–50.

[5] X. P. Burgos-Artizzu, P. Dollr, D. Lin, D. J. Anderson, and P. Perona, "Social behavior recognition in continuous video," in *IEEE Conf. on Computer Vision and Pattern Recognition*, June 2012, pp. 1322–1329.

[6] M. Amer, E. Bilgazyev, S. Todorovic, S. Shah, I. Kakadiaris, and L. Ciannelli, "Fine-grained categorization of fish motion patterns in underwater videos," in *IEEE Int, Conf, on Computer Vision*, Nov. 2011, pp. 1488–1495.

[7] W. Geng, P. Cosman, Z. Feng, C. Berry, and W.R. Schafer, "Automatic tracking, feature extraction and classification of C elegans phenotypes," *IEEE Trans. on Biomedical Engineering*, vol. 51, no. 10, pp. 1811–1820, Oct. 2004.

[8] E. Fontaine, D. Lentink, S. Kranenbarg, U. Mller, J. Leeuwen, A. H. Barr, and J. W. Burdick, "Automated visual tracking for studying the ontogeny of zebrafish swimming," *Journal of Experimental Biology*, vol. 211, pp. 1305–1316, 2008.

[9] J. Tian, A. Satpathy, E. S. Ng, S. H.G. Ong, W. Cheng, J.-M. Burgunder, and W. Hunziker, "Motion analytics of zebrafish using fine motor kinematics and multi-view trajectory," *Multimedia Systems*, vol. 22, no. 6, pp. 713–723, 2016.

[10] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971–987, Jul 2002.

[11] C.-C. Chang and C.-J. Lin, "LIBSVM: A library for support vector machines," *ACM Trans. on Intelligent Systems and Technology*, vol. 2, no. 3, pp. 1–17, Apr. 2011.

[12] C. M. Bishop, *Pattern Recognition and Machine Learning*, Springer, 2006.