3D Single Point Imaging Technology for Tracking Multiple Fish

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Abstract: Image based tracking like video tracking has shown potential in aquaculture behavioural studies in past decade. Image based tracking is allowing to have higher spatial and temporal resolution in compared to most conventional methods such as hand scoring, tagging and telemetry. They also permit to have more information about the environment rather than other methods. Most studies about trajectory are based on tracking in two dimensional (2D) environments; however, organisms are mostly included in three dimensional (3D) environments which influence ecological interactions extensively. Furthermore, in 2D image analysis, occlusion of fish is a frequent problem for analysis of fish tracking and ultimately their behaviour. Recently, new hardware based on single point 3D imaging technology have been developed which can provide 3D single points in real-time by combining a colour video camera, infrared video camera with an infrared projector. The main objective of this study was to develop a multiple fish tracking system in 3D space based on the current available 3D imaging technology. Developed system could accurately (98%) track multiple Tilapia (*Oreochromis niloticus*) which was freely swimming in an aquarium. This study contributes to feasibility of new sensors to monitor fish behaviours in 3D space.

1 INTRODUCTION

Aquatic organisms are very sensitive to alterations in the aquatic environment and they respond to changes with distinctive movement and behaviour (Little and Finger, 1990; Mancera et al., 2008). Monitoring of fish behaviour such as individual food intake and swimming speed not only can provide useful information for improving production management (Oppedal et al., 2011; Brown et al., 2006), but also it would help farmers to observe fish behaviour as a welfare indicator (Zion, 2012). Fish behaviour analysis can also be used for environmental risk assessment, like examining presence of chemical agents in water as an inexpensive and fast alternative to laboratory analysis (Kane et al., 2004; Masud et al., 2005; Xiao et al., 2015).

During past decade, machine vision system (MVS) as an alternative to conventional method, has been used for real-time and offline monitoring of fish behaviours such as schooling and shoaling (Salierno et al., 2007; Suzuki et al., 2003), novelty behaviours (Stewart et al., 2012), abnormality behaviours (Beyan and Fisher, 2013; Pinkiewicz et al., 2011), feeding behaviours (Parsonage and Petrell, 2003; Lee et al., 2013; Atoum et al., 2015) and respond behaviours to stress which caused by high stocking density (Papadakis et al., 2012) or hypoxic condition (Xu et al., 2006). In other words, MVS can provide automate, inexpensive, non-invasive and accurate information about fish behavioural parameters (Delcourt et al., 2012).

To date, a number of MVSs have been developed for studying individual fish behaviours. For instance, Kato et al., (2004) developed a system for quantifying individual Zebrafish (*Brachydanio rerio, Cyprinidae*) behaviours such as velocity, swimming distance, trace map and turning directions. Stewart et al. (2012) recorded individual fish behaviours in open filed test arenas to understand the fish novelty behaviours. Papadakis et al., (2012) developed low cost MVS to analysis fish behaviours in tank. However, tracking and monitoring multiple fish using MVS automatically have also been studied. For instance, Pinkiewicz et al., (2011) developed a system to record and analysis multiple fish movement using Kalman filter and data association techniques based on video footage of salmon in sea cage. Mirat et al., (2013) expanded a program called ZebraZoom to track larvae's Zebrafish movement. Perz-Escidero et al.,

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(2014) developed a visual system called idTracker for tracking individuals, even siblings, in a group based on finding fingerprint of each animal in a video recording of a group. Lee et al., (2014) developed a MVS based on particle filter algorithm for tracking multiple fish in a single tank.

Most studies about trajectory are based on tracking in two dimensional (2D) environment; however, most organisms are included in three dimensional (3D) environment, which influence ecological interactions extensively (Pawar et al., 2012). For instance, it would be difficult to recognize some behaviours that contain vertical movements (Horodysky et al., 2007). Moreover, occlusion is a frequent problem for analysis of fish tracking and ultimately their behaviour where 2D images are using for analysis. Therefore, tracking animal in their 3D environment is more desired as a promised method in animal behavioural studies.

Tracking system in 3D has studied using different approaches such as light field video cameras which composite optics are used to simultaneously capture images focused at different distance from lens, therefore allowing to reconstruct scene in 3D (Matsumoto et al., 2013), or single image of reflections or shadows from surface of a 3D surface such as spherical mirror (Kanbara et al., 2006; Chen et al., 2011). Nevertheless, multiple cameras are usually employed to reconstruct 3D scene for tracking objects. For example, Spitzen et al., (2013) used two monochrome couple- charged device (CCD) video cameras to study in-flight behaviour of individual malaria mosquito to human odor and heat in 3D space. Cachat et al., (2011) reconstructed 3D environment using images from two video cameras, and manually recorded position of individual Zebrafish to understand neurophenotyping of adult Zebrafish in 3D environment. Some other researchers also tried to track multiple objects using multiple cameras. Viscido et al., (2004) used stereo vision system to track 4 to 6 group of giant danios (*Danio aequipinnatus*). Veeraraghavan et al., (2006) proposed a method based on motion information to track multiple bees using two video cameras. Wu et al., (2011) developed an algorithm by solving three linear assignment problems for tracking multiple fruit fly using two video cameras automatically. Synchronizing multiple cameras usually need different hardware and complicated software; they also need more handlings, which may affect animal behaviours (Dell et al., 2014). Besides, spatial resolution of images are dramatically drops when objects move away from sensors (Gokturk et al., 2004).

Recently, new hardware based on single point 3D imaging technology (e.g. Microsoft Kinect or Asus's Xtion Pro) have been developed. This hardware can provide 3D single points in real-time by combining a colour video camera, infrared video camera with an infrared projector to create defined infrared laser light pattern which depth information can be obtained. These new hardware practically provide possibility to develop an affordable tracking system to study multiple fish in real-time. So, the main objective of this study was to develop a multiple fish tracking system in 3D space based on the aforementioned sensor. To the best of our knowledge, no research has been done on examining this technology for fish tracking. The introduced system was able to resolve the occlusion problem and track each fish separately even the siblings in real-time 3D space.

2 MATERIALS AND METHODS

2.1 Experimental Setup

The experiment took place at Laboratory of Signal and Image Processing of Institute of complex systems, FFPW, University of South Bohemia, Czech Republic. Tilapia (*Oreochromis niloticus*) was selected for demonstrative purpose in this study. Tilapia has been used in many studies as the experimental model for behavioural studies because of its well characterized responds to stress (Moreira and Volpato, 2004). Standard length (SL), between the front head extremity and the insertion of the tail fin, and body height (BH), in front of the first ray of the dorsal fin, as morphometric parameters were measured. Fish selected for this study had 8.6, 8.4, 8, 8 cm SL and 2.6, 2.5, 2.5, 2.4 cm BH respectively. The glass aquarium (60 cm ×30 cm ×29 cm, 10 cm water depth) with transparent sides was used for recoding fish activities. In order to avoid water surface movements that could create light reflection, Microsoft Kinect v1 was placed under the tank from a stationary (70 cm) in centre of the aquarium and vertical position, which sensor was faced to the aquarium. This distance was selected to maintain the most field of view (FoV) of Microsoft Kinect v1, which is 43° vertically and 57° horizontally and increase the depth resolution (Khoshelham and Elberink, 2012).

Tilapia is changing its skin colour quickly based on ambient colour in background, which causes low contrast between fish and background. Therefore, in order to have high contrast between fish and background for better post processing such as segmentation, Blue Bristol board was used as background (Xu et al., 2006).

Video was recorded for 30 minutes using software which has been developed especially for this study by authors with maximum sample rates of 10 frames per seconds (fps) and then converted to image sequence for further processing. Four 30-minute video sequences that recorded one, two, three and four individuals were totally prepared. The Experimental aquarium was indirectly lit by two lamps, which provide low light intensity.

RGB Images from the Microsoft Kinect v1 were recorded in portable network graphics (PNG) format with spatial resolution of 480×640 pixel. Images have three components (namely red, green and blue) with each colour comprising 256 graduations. Depth raw data were also recorded in 11-bit format resolution. Figure 1 shows the schematic of recording setup. The depth images are constructed by triangulation from IR image and the projector and carried by IR image. In other words, a 3D coordinate point of depth images (X_{3D}) is constructed from the measurement of [x, y, z] in depth image as below, which has been described by Smisek et al., (2011):

$$X_{3D} = \frac{1}{c_1 d + c_0} dis^{-1}\left(K_{IR}^{-1}\begin{bmatrix} x + u_0 \\ y + v_0 \\ 1 \end{bmatrix}, k_{IR}\right) \quad (1)$$

Where K_{IR} is Infrared camera calibration, k_{IR} is distortion parameter of the IR camera, c_1 and c_0 are parameters of the model, *dis* is distortion, u_0 and v_0 are mean value of shift position from IR to Depth camera (u_0 = 3.0 and v_0 = 2.9), and are projected to the RGB image as below:

$$u_{RGB} = K_{RGB}\, dis\, (R_{RGB}\, (X_{IR} - C_{RGB}),\, k_{RGB}) \quad (2)$$

where *dis* is distortion function, k_{RGB} is distortion parameter of the RGB camera. R_{RGB} is the rotation matrix, K_{RGB} is calibration matrix and C_{RGB} is the centre of RGB camera.

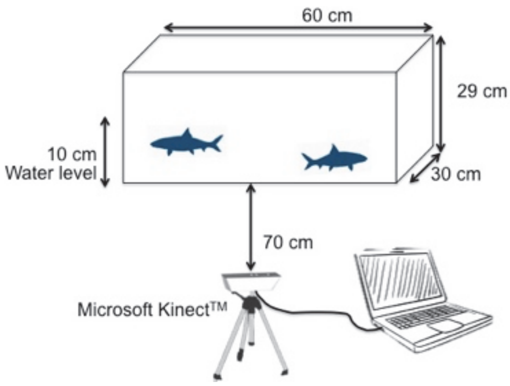


Figure 1: Schematic of single point 3D multiple tracking system.

2.2 Pre-processing

Microsoft Kinect's RGB images were converted to Hue, Saturation, and Value (HSV) colour model using method described by Tang et al., (2003). HSV colour model provides immunity to illumination condition. Once after the conversion, segmentation process was performed to remove unwanted pixels. Moreover, some morphological operations such as erosion and dilation have been performed to eliminate the segmentation noises. All of the images were processed using Matlab Image processing toolbox.

2.3 Image Processing

Real world X and Y of centroid of multiple tilapia were obtained using the method proposed by Pérez-Escudero et al., (2014). The method is a multi-tracking algorithm based on extracting of characteristic fingerprint from each object in a video recording of a group, from RGB images. First, a set of the reference images was extracted, which fish were separated. Then, algorithm compared reference images with images, where fish were connected. To obtain clear fingerprint for each fish, intensities of two pixels (I_1, I_2) separated in *d* distance, were determined in each frame, and then were used to identify each fish in all frames. Moreover, algorithm aggregated the information of all images that belong to the same individual, while it moved without crossing with any other individual. This will improve the probability of correct identification of each individual. Depth information (z-value) was also extracted from Kinects' depth image; first converting resolution of images from 11 bit to 8 bit, then transformed to 3D point cloud using Matlab image processing toolbox. Finally, fish trajectories, were extracted based on 3D location of each fish in each frame.

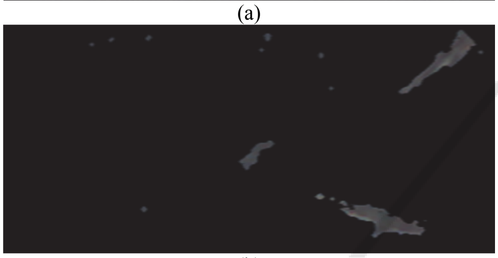
2.4 Accuracy Assessment

The proposed system is acquiring the trajectory automatically, thus it is important to assess the accuracy of the result respectively. Accuracy and precision of the system was evaluated by comparing results with ground truth. Human inspection was used to evaluate 2D track produced by using finger printing method frame by frame, and then associating the 3D position between each consecutive frames to form complete trajectory.

3 RESULTS AND DISCUSSION

The proposed system was applied to four 30-minute video sequences that were recorded one, two, three and four individuals. Figure 2 shows the original and pre-processing image frame. Fish were successfully segmented in most frames from the background. Any remained noise pixels, which remained, were removed using morphological operations.

(a)



(b)

(c)

Figure 2: Experiment images and processing results, (a) original image from Microsoft Kinect in RGB bands, (b) segmented image and (c) segmented image after correction.

Before constructing trajectory in 3D space, initially we first tracked individual fishes in 2D space in each frame using Pérez-Escudero et al., (2014) proposed method. Depth information (z-value) from each individual was extracted after tracking fish in 2D space using both systems. Figure 3 shows the trajectory of four fish in 3D space using both sensors.

Proposed system was successfully tracked multiple fish with 98% accuracy. The obtained 3D coordinate estimation accuracy was similar to the accuracy that could be obtained from stereo vision type systems as convention system for determining 3D coordinates (Torisawa et al., 2011). However, decreasing in accuracy of the proposed tracking system is expected with increasing in number of tracking objects. The results of this study indicated that the single point 3D imaging technology could be employed for fast, accurate, inexpensive and non-invasive multiple fish tracking even under sever occlusion. The proposed system added length of third dimension (z-value) for not only improving the precision but also for shedding light on animal activity in 3D environment which were the limitation for previous systems (Delcourt et al., 2006).

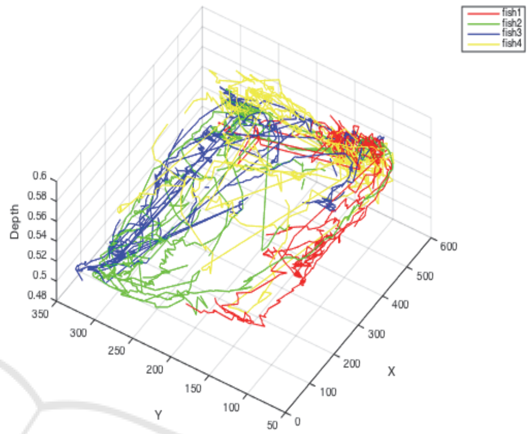


Figure 3: 3D Trajectory acquisition results of four fish from a 10-minute video using in 3D.

Single point 3D imaging offers information with less computational and power consumption, which make it ideal technology for monitoring in real-time with less handling process. However, current available single point 3D imaging hardware have some limitations which make them difficult to use in commercial scale. For instance, Khoshelham and Elberink (2012) pointed out for tracking and mapping object(s) using Kinect with high resolution, the data should be acquired within 1-3 m distance to the sensor, which makes remote sensing application of sensor to 3 meter. The number of animals which can be tracked using Kinect is also limited to how many fish will be fitted in the FoV of the camera (Schramm, 2010).

4 CONCLUSIONS

This study developed an automatic system for accurate tracking of multiple fish in 3D environment even under severe occlusion. The system was based on fingerprinting that track individual fish in 2D space and depth information which was provided by depth sensor in Microsoft Kinect. The results of the system evaluation showed that the introduced system was able to track multiple fish in an aquarium even under sever occlusion successfully. However, current available 3D single point imaging system has some limitations but it would be expected to be used in near future as an ideal sensor for monitoring and recording animal behaviour in 3D space in real-time when study is conducted in small environments such as aquariums.

Proposed system could be extended further for studying fish behaviours by evaluating more states such as speed and inter-individual spacing. It can also be used to study individual fish behaviour in 3D space in a group which would provide useful information about fish schooling. It would be necessary to understand the maximum number of fish which can be tracked using the introduced system, which future research may need to answer this question.

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