Paper:

Stereo Vision 3D Tracking of Multiple Free-Swimming Fish for Low Frame Rate Video

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3D multiple fish tracking has gained a significant growing research interest to quantify fish behavior. However, most tracking techniques have used a high frame rate that is currently not viable for real-time tracking applications. This study discusses multiple fish tracking techniques using low frame rate sampling of stereo video clips. The fish are tagged and tracked based on the absolute error of predicted indices using past and present fish centroid locations and a deterministic frame index. In the predictor sub-system, the linear regression and machine learning algorithms intended for nonlinear systems, such as Adaptive Neuro-Fuzzy Inference System (ANFIS), symbolic regression, and Gaussian Process Regression (GPR), were investigated. Results have shown that in the context of tagging and tracking accuracy, the symbolic regression attained the best performance, followed by the GPR, i.e., 74% to 100% and 81% to 91%, respectively. Considering the computation time, symbolic regression resulted in the highest computing lag of approximately *946 ms* per iteration, whereas GPR achieved the lowest computing time of *39 ms*.

Keywords: Multiple Object Tracking, Fish Tagging and Tracking, Multigene Genetic Programming, ANFIS, Gaussian Process Regression, Stereovision

1. Introduction

Computer vision using 2D images has been widely used to detect specific objects, such as plants, fruits, vehicles, people, face recognition, animals, character recognition and vehicles, among others [1]–[4]. It is also widely used for multiple object tracking (MOT), such as vehicles, animals, people and plant phenotyping [2][5]. Through computer vision, MOT is also deemed one of the significant recent advances in fish behavioral biometrics monitoring, such as anomaly detection, fish appetite and responses to environmental conditions [6]–[8]. In addition, 2D tracking, using a single camera to capture images from either the top view or side view of fish containers and cages, is an efficient way for the individual monitoring of a single fish in a tank [9][7].

The considerable challenge of individual fish monitoring using 2D tracking is caused by frequent occlusions when multiple fish are in the scene. Most of the studies use a Kalman filter and particle filter to track the fish during the occlusions by predicting the individual trajectory. In a general 2D multi-object tracking, the Kalman filter, particle filter and extended Kalman filter are also popularly used for probabilistic inference to predict the trajectory of the target objects on the next frame, based on their previous states [5]. Recently, the idTracker algorithm has been deemed the most accurate 2D video-based multiple animal trajectory tracker, including fish, which significantly reduces the tracking error caused after occlusion [6][10].

Predominantly, 3D or stereo vision tracking using binocular cameras offers better advances in MOT, with an additional depth information to reduce the error caused by frequent occlusion [11]–[13]. In fish tracking, the work of [14] introduced a new approach of multiple tracking by iteratively matching the seemingly similar motion continuity between the detected fish from perpendicular epipolar stereo images. It resulted in a tracking accuracy of around 80% and is superior to prior approaches, such as [11]–[13], but is open for improvement. Specifically, [15] and [17] used a greedy search algorithm to track high-density fish, while [16] detected the fisheye and tracked the fish using a 2D Kalman filter and 3D reconstruction via master-slave association of synchronized images. However, the approaches of [10]–[13] used high frame rates with at least approximately 90 fps video clips and high-resolution images. Considering all the processing involved in image acquisition, storage, enhancement, fish detection and tracking [18] [19], it is not suitable for real-time applications and necessitates sophisticated hardware and computing algorithms.

This study introduces a new approach of individual multiple fish 3D tracking using a synchronized pair of

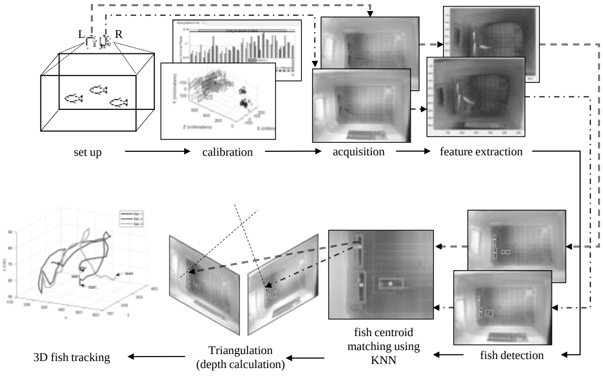

Figure 1: Overall Process Flow of Fish Tracking

low frame rate video sampling. Further, this study explores the tracking algorithm commonly used for dynamic prediction ranging from simple linear regression to nonlinear models such as evolutionary and learning algorithms. The linear model is deemed applicable for object movement with a steady velocity and acceleration transition over successive frames, while nonlinear models are considered to attain superior affinity between tracklets for nonlinear moving objects [5], such as free-swimming fish.

2. Methodology

The overview of the process flow of this paper's framework is shown in Figure 1.

2.1. Set up, Calibration and Image Acquisition

There are three free-swimming fish in a 73 x 52 x 44 cm^3 container tank with clear water in natural outdoor lighting condition. Two identical webcams were placed above the tank, 10 cm apart, and directly wired to the PC server. These webcams were calibrated using Stereo Camera Calibrator in MATLAB 2019b with 25 captured image pairs of 9 mm, 19 x10 checkerboard squares placed at different positions. The synchronized video clips of the left and right webcams were obtained using the Image Acquisition Toolbox in MATLAB and were set to capture 30 fps with 640x480 pixels. The 10-second video clips were used and sampled every 8th frame. It follows that the frame sampling rate used in this paper is approximately 4 fps.

2.2. Fish Segmentation and Detection

The sampled RGB images obtained from two webcams were converted to HSV at $f(x,y)$, wherein x and y denote the 2D dimension of images with pixel values of $\{x \in \mathbb{R} | 0 \le x \le 1\}$ and $\{y \in \mathbb{R} | 0 \le y \le 1\}$. Then, the images were binarized using the lower and upper thresholds, $T_{SL} = 0.38$ and $T_{SU} = 0.7$, in the saturation channel, respectively, wherein the set thresholds were based on the histogram of the HSV image. In essence, the detected pixels of the fish area and background pixels were set to $b_1 = 1$ and $b_0 = 0$, respectively. Given the thresholds, the binarized segmented images can be represented by Eq. (1).

$$f_{sT}(x_{sT}, y_{sT}) = \begin{cases} b_1, & T_{SL} < f(x,y) < T_{SU} \\ b_0, & otherwise \end{cases} \quad \text{...........}(1)$$

To further enhance the binary images, noises, such as small objects, were removed and light structures were suppressed. Then, the centroids of the detected fish from the binarized images, $f_c(x_c, y_c)$, were calculated and used as the locations of the fish. It follows that the centroid in each detected fish in the binary image can be determined as the average of all the pixel locations, i_b, in a blob with $b_1 = 1$, as depicted in Eq. (2).

$$f_c\left(\frac{1}{n_b - i_b + 1}\sum_{i_b}^{n_b} x_i, \frac{1}{n_b - i_b + 1}\sum_{i_b}^{n_b} y_{i_b}\right) \text{............}(2)$$

2.3. Matching of Fish from Stereo Images and Determination of Depth

To match the three fish from stereo images, the *k*-nearest neighbor (KNN) algorithm was used to find the closest fish centroid in the left image for every query of the detected fish centroids in the right image. Then, the closest centroids were paired and deemed as similar fish, as depicted in Figure 2. Given the paired fish centroid sets, the depth, z_c, is calculated using triangulation and the parameters from the calibrated information of the two webcams.

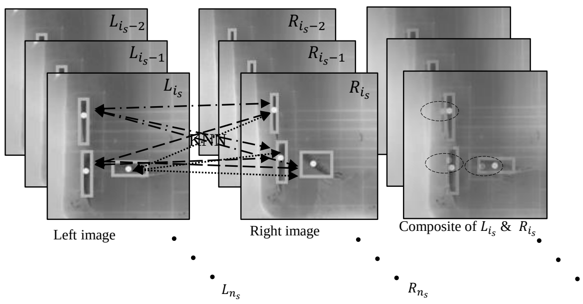

Figure 2: Matching of Fish in Stereo Images using KNN

2.4. Datasets, Tagging and Tracking Scheme

A pair of stereo video clips at 30 fps was used with a total of 313 frames at $\{i_f \in \mathbb{N} | 1 \le i_f \le 313\}$, where i_f is the index number of frames. The video clips were then sampled every 8th frame. It follows that the new frame index sampling is denoted by $i_s = 8i_f - 7$. With the frame sampling, the dataset for analysis was reduced by 87%, i.e., $\{i_s \in \mathbb{N} | 1 \le i_s \le 40\}$. The dataset was then divided for training and checking, as in Eqs. (3) and (4), respectively, wherein P represents the input variables of the fish centroid locations (x, y, z), and Q is a dependent variable, which is equivalent to the corresponding index sampling frame, i_s.

$$T_d = (P_t, Q_t) \quad \text{at} \quad i_{s-4}, i_{s-2}, i_s \text{.....................}(3)$$
$$C_d = (P_c, Q_c) \quad \text{at} \quad i_{s-5}, i_{s-3}, i_{s-1} \text{...................}(4)$$

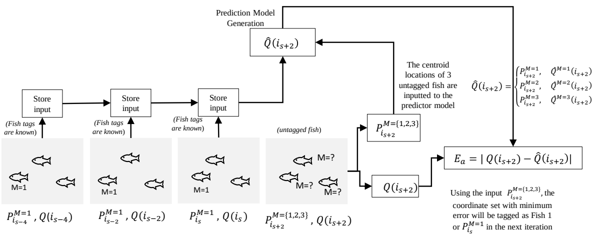

Figure 3: Fish Tagging and Tracking Algorithm (Example of Tagging for Fish 1)

Specifically, to tag the fish in each frame, the Q_t at i_{s+2} must be predicted given the past three tracklets of fish centroids in the subsequent frame, i.e., $\hat{Q}(i_{s+2})$. The actual untagged data on the $P^{M=\{1,2,3\}}_{i_{s+2}}$, where M represents the tagged fish indices, will be used as an input for the frame index predictor $\hat{Q}(i_{s+2})$. $Q(i_{s+2})$, or simply i_{s+2}, which is deemed to be deterministic, will then be compared to $\hat{Q}(i_{s+2})$. Finally, as per Eq. (5), the least absolute error, ε_a, or difference between $\hat{Q}(i_{s+2})$ and $Q(i_{s+2})$, will serve as the tagging reference of the three fish. Figure 3 shows the illustrative process flow of the tagging and tracking algorithm for fish at $M = 1$. To tag the fish for $M = \{2,3\}$, the process is repeated.

$$\varepsilon_a = \left| Q(i_{s+2}) - \hat{Q}(i_{s+2}) \right| \ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

2.5. Prediction Algorithms

Generally, the prediction model for $\hat{Q}(i_s)$ uses the independent variable – the fish centroids past locations $P(x, y, z)$ – and the corresponding dependent variable $Q(i_s)$ to estimate $\hat{Q}(i_{s+2})$ using the centroids in the input frames at i_{s+2}, as in Eq. (6) and Figure 3.

$$\hat{Q}(i_{s+2}) = P\left(x_{i_{s+2}}, y_{i_{s+2}}, z_{i_{s+2}}\right) \ldots\ldots\ldots\ldots\ldots(6)$$

2.5.1. Multiple Linear Regression

Linear regression is the simplest and most commonly used method for the prediction or estimation of variables with a linear relationship. Here, linear regression was used to estimate the frame index, $\hat{Q}(i_{s+2})$, given the 3D locations of the fish centroids, wherein β_0 is the intercept term while $\beta_1, \beta_2, \beta_3$ are coefficients of each independent variable, as described by Eq. (7).

$$\hat{Q}(i_{s+2}) = \beta_0 + \beta_1 x + \beta_2 y + \beta_3 z + \varepsilon \ \ldots\ldots\ldots(7)$$

2.5.2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The ANFIS is a hybrid algorithm that learns the relationship between input and output through the integration of artificial neural network (ANN) and fuzzy logic principles. Presently, it is a popular artificial intelligence technique and has a wide range of applications for nonlinear optimization problems and dynamic prediction [20]. The main advantage of ANFIS over ANN is that it eliminates the black-box relationship between input and output by using the comprehensible fuzzy rules and membership functions [20]–[22]. In this study, two clustering methods were used – subtractive clustering (SCM) and fuzzy c-means clustering (FCM) to cluster the membership of input data. For SCM, the cluster influence range was set to 0.25, while for FCM, the number of clusters was set to 2. The generalized learned structures for ANFIS-SCM and ANFIS-FCM using the given datasets – T_d, C_d and the specified clusters – are shown in Figure 4.

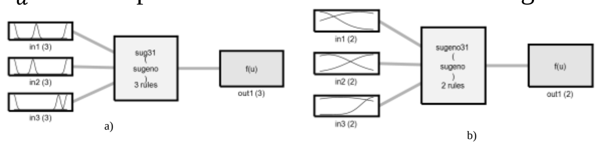

Figure 4: ANFIS Structures: a) SCM, b) FCM

2.5.3. Gaussian Process Regression (GPR)

GPR is another widely-known machine learning regression model for nonlinear predictions through the non-parametric Bayesian approach [23]. The predictor, $\hat{Q}(i_{s+2})$, is estimated as the noise value of $P\left(x_{i_{s+2}}, y_{i_{s+2}}, z_{i_{s+2}}\right)$, wherein the noise distribution is a Gaussian, $\mathcal{N}(0, \sigma^2)$, with a variance of σ^2.

$$\hat{Q}(i_{s+2}) \sim \mathcal{N}\left(P\left(x_{i_{s+2}}, y_{i_{s+2}}, z_{i_{s+2}}\right), \sigma^2\right) \ldots\ldots\ldots\ (8)$$

2.5.4. Multigene Genetic Programming (MGGP)

MGGP, also known as symbolic regression, is a nonlinear regression model based on evolutionary genetic searches of mathematical symbolic expression [24]. This algorithm provides equations to describe the input-output relationship between the trained parameters instead of the black-box approach derived from other machine learning models [25]. Since the symbolic regression is obtained from genetic programing, through evolutionary search to generate the optimal solution, the parameters depicted in Table 1 were utilized and run via GPTIPS – a symbolic regression platform that is pluggable in MATLAB.

Table 1: Configuration for Multiple Gene Symbolic Regression

Run parameter	Value
Population size	10
Max. generations	20
Generations elapsed	20
Input variables	3
Training instances	3
Tournament size	7
Elite fraction	0.7
Probability of pareto tournament	0.7
Max. genes	2
Max. tree depth	5
Max. total nodes	Inf
ERC probability	0.1
Crossover probability	0.84
Mutation probabilities	0.14
Complexity measure	Expressional
Function set	TIMES MINUS PLUS

2.6. Evaluation Metrics

The tagging and tracking of the three fish will be evaluated using a confusion matrix such as precision, recall, F1-score and accuracy, as described by Eqs. (9)-(12), wherein TP, TN, FN and FP are the true positive, true negative, false negative and false positive counts, respectively. In addition, the root-mean-square error (RMSE) between the actual frame index, Q_i, and the predicted frame index, $\hat{Q}_i$, is also evaluated.

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

$$F1-score = \frac{2 \times Precision \times Recall}{Precision+Recall} \quad (11)$$

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \quad (12)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Q_i-\hat{Q}_i)^2}{N}} \quad (13)$$

3. Results and Discussions

3.1. Overall Tagging and Tracking Score

The tagging and tracking result of the three fish is depicted in Table 2, wherein the regression-based algorithms, either linear- or nonlinear-based, are generally superior compared to the ANFIS predictors. The ANFIS-SCM attained the lowest accuracy, followed by ANFIS-FCM. Considering the regression-based algorithms, linear regression attained the lowest tagging and tracking F1-score, while MGGP achieved the highest scores, followed by GPR.

Considering the RMSE, GPR attained the closest predictor result, compared to the MGGP, by seven points. Therefore, in an environment wherein a higher fish density is present in a tank, GPR might be considered more suitable than MGGP in terms of correct tagging scores since it attained a more accurate prediction.

3.2. Computation Cost

The computing time for the generation of prediction algorithms during the training, testing and tagging of fish is also evaluated at every iteration. In order to account for the computational time for the prediction and tagging algorithms, the time expended for segmentation and detection of the fish in the sampled frames is not included. Results have shown that, although the symbolic regression, or MGGP, attained the overall highest accuracy of fish tagging, the computational time of MGGP was higher by 96%, compared to GPR. Further, GPR attained the lowest computational time over other algorithms. Considering real-time applications, GPR has shown a favorable result.

3.3. Fish Movement Profile and Tagging Score

According to the study in [5], social force, or interaction between objects for both individual and group, can affect tracking performance, which is primarily determined by velocity and acceleration. Figure 5 shows the speed and acceleration profile for the three fish with respect to tagging score using the different prediction algorithms. As can be seen, Figure 5(a) has no consistent occurrence of false-negative tags concerning the specific frame for three fish. Considering speed, the second fish has the fastest speed with the lowest deviation, while the first and third fish have nearly equal speed medians and deviation. With regard to acceleration, the third fish has the highest acceleration with the lowest deviation.

By correlating the speed and acceleration to the fish tagging's F1-score using different prediction algorithms, only MGGP attained a strong correlation

Table 2: Result of Fish Tagging and Tracking using the Different Prediction Algorithms

Algorithm	Fish ID	Computation time per iteration (ms)	RMSE	TP	FN	FP	TN	Precision	Accuracy	Recall	F1-Score
Linear Regression	Fish 1	49	44.91	30	4	4	64	88.24%	92.16%	88.24%	88.24%
	Fish 2	49	25.02	29	5	5	63	85.29%	90.20%	85.29%	85.29%
	Fish 3	53	125.06	24	10	10	58	70.59%	80.39%	70.59%	70.59%
	Overall	***50***	***65.00***	***83***	***19***	***19***	***185***	***81.37%***	***87.58%***	***81.37%***	***81.37%***
ANFIS-SCM	Fish 1	147	31.19	18	36	6	42	75.00%	58.82%	33.33%	46.15%
	Fish 2	141	46.36	15	21	16	50	48.39%	63.73%	41.67%	44.78%
	Fish 3	144	39.13	13	34	14	41	48.15%	52.94%	27.66%	35.14%
	Overall	***144***	***38.89***	***46***	***91***	***36***	***133***	***56.10%***	***58.50%***	***33.58%***	***42.01%***
ANFIS-FCM	Fish 1	130	44.91	29	7	4	62	87.88%	89.22%	80.56%	84.06%
	Fish 2	133	25.02	28	6	6	62	82.35%	88.24%	82.35%	82.35%
	Fish 3	127	125.06	23	11	11	57	67.65%	78.43%	67.65%	67.65%
	Overall	***130***	***65.00***	***80***	***24***	***21***	***181***	***79.21%***	***85.29%***	***76.92%***	***78.05%***
Gaussian Process Regression	Fish 1	39	21.96	31	3	3	65	91.18%	94.12%	91.18%	91.18%
	Fish 2	39	19.02	31	3	3	65	91.18%	94.12%	91.18%	91.18%
	Fish 3	39	19.04	28	8	5	61	84.85%	87.25%	77.78%	81.16%
	Overall	***39***	***20.00***	***90***	***14***	***11***	***191***	***89.11%***	***91.83%***	***86.54%***	***87.80%***
Symbolic Regression	Fish 1	991	22.99	30	4	4	64	88.24%	92.16%	88.24%	88.24%
	Fish 2	818	10.07	34	0	0	68	100.00%	100.00%	100.00%	100.00%
	Fish 3	1030	48.16	27	7	7	61	79.41%	86.27%	79.41%	79.41%
	Overall	***946***	***27.07***	***91***	***11***	***11***	***193***	***89.22%***	***92.81%***	***89.22%***	***89.22%***

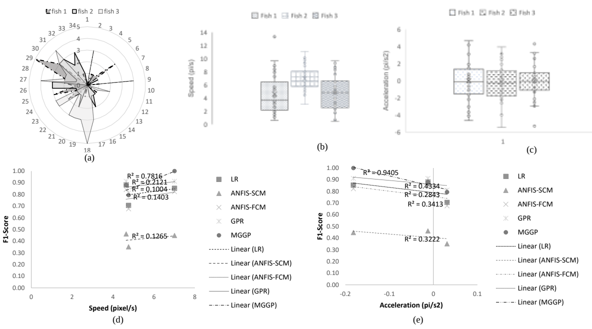

Figure 5: Fish Tagging and Tracking Profile: **a)** Overall Cumulative Count of False Negatives using different Algorithms per Image for Three Fish, **b)** Boxplot of Fish Speed, **c)** Boxplot of Fish Acceleration, **d)** Scatterplot of Fish Speed and Tagging F1-Score using Different Prediction Algorithms, **e)** Fish Acceleration and Tagging F1-Score using Different Prediction Algorithms

between the speed F1-score and acceleration F1-score (refer to Figures 5(d) and 5(e), respectively). It is worth noting that MGGP reached a 100% F1-score for the 2nd fish, wherein the speed is high but with less dispersion. Moreover, MGGP attained a low F1-score on the 3rd fish for which the acceleration was highest among other fish. For other prediction models, the fish motion and tagging score attained a weak correlation.

4. Conclusion

The multiple fish 3D tracking in low frame rate stereo videos attained a good score from 79% to 100% using MGGP, and 81% to 91% using GPR. In contrast, the ANFIS-based algorithms attained worse tracking performance than linear regression. In the context of computation cost, GPR attained the fastest computation time, 39 ms, with a considerable tracking score, whereas MGGP had the longest computation time of approximately 946 ms per iteration.

Moreover, fish motion speed and velocity were highly correlated to the tracking score for MGGP but attained weak correlation using the other algorithms. Future work should include further investigation of multiple fish tracking, including fish motion (such as the speed and acceleration) and improve the tracking technique for a higher fish population and through a longer observation time.

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- 2015 to 2017 -Master of Engineering in Electronics and Communications Engineering, University of San Carlos
- 2017 to present – Faculty, Cebu Technological University

Main Works:
- Towards Tracking: Investigation of Genetic Algorithm and LSTM as Fish Trajectory Predictors in Turbid Water.

Membership in Learned Societies:
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- 2021 – Completed Ph.D. in Electronics and Communications Engineering, De La Salle University, Manila

Main Works:
- Integration of non-destructive vision system with biosystem to yield sustainable and high yield agricultural crops

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Main Works:
- Hybrid Data Acquisition Network for Precision Farming

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- Graduate Student of M.Sc. in Electronics and Communications Engineering, De La Salle University

Main Works:
- Fuzzy Irrigation System with Rain Detection and Fertilizer Control

Membership in Learned Societies:
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Brief Biographical History:
- 2017 – 2019 Hardware and Software Engineer, ITX Electronics Pte. Ltd. (Singapore)
- 2019 – Present MS ECE Student, De La Salle University

Main Works:
- An Image Classifier for Underwater Fish Detection using Classification Tree-Artificial Neural Network Hybrid

Membership in Learned Societies:
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Brief Biographical History:
- 2014 Graduated Ph.D. in Electronics and Engineering, De La Salle University

Main Works:
- Quadrotors-swarm behavior for aggregation, foraging, formation and tracking

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- 2014 Graduated Ph.D. in Electronics and Engineering, De La Salle University

Main Works:
- Swarm Intelligence for Underwater Swarm Robot System

Membership in Learned Societies:
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Brief Biographical History:
- 1996 Graduated Ph.D. in Electronics and Engineering, De La Salle University

Main Works:
- Development and Design of Mobile Robot with IP-based Vision System

Membership in Learned Societies:
- Institute of Electrical and Electronics Engineers (IEEE)

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Brief Biographical History:
- 1996 Received the Doctor of Philosophy at Loughborough University

Main Works:
- "Fuzzy Logic – Controls, Concepts, Theories and Applications" ISBN 978-953-51-0396-7

Membership in Learned Societies:
- Institute of Electrical and Electronics Engineers (IEEE)

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Brief Biographical History:
- 1986 Awarded PhD from Imperial College, University of London

Main Works:
- Artificial Neural Networks in Cancer Diagnosis, Prognosis and Patient Management.
- Digital Filters in One and Two Dimensions: Design and Applications. i

Membership in Learned Societies:
- Institute of Electrical and Electronics Engineers (IEEE)

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