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RGB-based Early Detection System of Drowning Person using Machine Learning Vision assisted GMM-FSM Framework for Real-time Drowning Detection

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Abstract

Drowning is one of the leading causes of accidental death worldwide, particularly among children and individuals in swimming environments. Despite advancements in surveillance and monitoring technologies, early detection of drowning incidents remains a major challenge due to visually complex aquatic environments, dynamic backgrounds, and swimmer interactions. Existing systems often fail to identify early behavioral symptoms or generate high false alarm rates, limiting their reliability for real-time safety applications. In this study, a novel vision-based framework is proposed for early detection of drowning incidents in swimming pools. A key challenge addressed in this work is the high noise level in foreground detection and behavior recognition caused by water reflections, background variations, and crowded scenes. To overcome these limitations, visual distress indicators and motion-based foreground descriptors are integrated to improve early identification of drowning behavior. The proposed system consists of two primary components: a vision module and an event-inference module. The vision module employs a model-based approach to accurately detect, segment, and track swimmers under varying illumination and scene conditions. The event-inference module utilizes a finite state machine to analyze swimmer motion patterns and identify abnormal behavioral transitions associated with drowning. Additionally, a sequential change detection mechanism is incorporated to enable rapid and reliable incident identification. Experimental evaluation on multiple video sequences, including simulated drowning scenarios, demonstrates that the proposed system achieves over 90% detection accuracy while maintaining low false alarm rates, confirming its effectiveness for real-time drowning prevention and aquatic safety monitoring applications.

Keywords: Drowning detection, Vision-based, Sequential modification, Hidden Markov Models (HMMs), Gaussian mixture model.

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1. Introduction

Swimming is the favorite sport, but in the water, beginners often cannot breathe freely causing suffocation, then losing balance and leading to a drowning accident. Some special situations, such as cramps, can collide with mutual illness or mental stress can also cause swimmers to drown. Swimming is one of the major causes of child death and disability. Worldwide, drowning produces a higher mortality rate than any other reason. Worldwide, drowning produces a higher mortality rate than any other reason [1], [2]. Children under the age of 15 mostly are injured in unattended swimming pools, while younger children are particularly vulnerable. Recent studies emphasize that drowning prevention requires early detection and rapid response, and that vision-based AI systems are increasingly being explored for real-time monitoring in pools and beaches [1], [3], [5], [36]. The earliest swimming alarm system appeared in 1976 and for some patent applications, but for various reasons, these technologies are not popular [2], [30]. In 2001, the French visual IQ company produced the world's first drowning alarm system Poseidon, which is the first commercial promotion system.

The modern world, human behavior analysis with automated video monitoring is a very effective technique for quickly identifying the presence of any odd occurrences in our immediate environment [4]. The technological hurdles that must be overcome include the need to consistently recognize and track moving objects against a potentially changing background, as well as the development of an in-

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ferential module that converts targets' behavioral patterns into incidents with semantic relevance. In light of the current surge in demand for these technologies in application scenarios, such as public safety, automatic detection, and tracking systems, researchers are focusing their efforts on developing systems that can detect and avoid threats [9], [10].

The drowning system operates in environments that are more realistic than indoor and controlled outdoor environments [6], [7], which are typical of those encountered in real-world applications [19] – [21]. For example, although most state-of-the-art systems have improved in recent years, they continue to encounter significant obstacles owing to constantly changing ambient illumination, vastly dynamic backgrounds, and low discernibility of targets [34].

Drowning detection device is precious for lifeguards and can be used in an unsupervised pool to improve the overall safety of the pool environment. Previously published work on automated water surveillance systems for drowning detection has been restricted to a few disclosed systems and practical implementations, including underwater and overhead camera-based solutions [2], [33]. The dependence on underwater cameras in these systems comes with many drawbacks, including 1) high installation costs and occultation of the other swimmers, and 2) the detection of drowning victims is limited to victims who have fallen to the bottom of the pool [2].

As a result, any rescue operation might be launched far sooner than those who are now trapped. One of the most difficult technological challenges that must be overcome in the case under consideration is the precise detection and tracking of swimmers in high outdoor aquatic environments [28]. Novel block-based background modeling and thresholding with hysteresis approaches are being developed to successfully identify and segment swimmers in real-time [33]. The block-based background modeling technique used in this study successfully captures the spatial relationships and dynamic character of the aquatic environment. As opposed to this, the thresholding with-hysteresis approach handles the challenge of setting thresholds within a background subtraction framework, which is intended to give great sensitivity in the detection of swimming subjects, while simultaneously reducing the background noise. With the creation of a unique occlusion management technique, the system also has the facility of handling incomplete occlusions in the future.

Unlike the former proposal which mainly took into account the spatial distance and geometrical characteristics, our proposed system incorporates the MRF framework that takes into account both spatial and time characteristics leading to better performance and strength of the system in the diverse and dynamic aquatic settings. The adoption of a new functional link network, integrating the swimmer characteristics gathered in an optimal manner, has demonstrated some encouraging conclusions in detecting water emergencies. As it has been stated in the study results, such a method of descriptors fusion is far more effective in comparison to the hierarchical approach proposed in [30].

Key contributions of the paper:

1. Developed an RGB camera-based system for the early detection of drowning events using overhead video input, eliminating the need for underwater or wearable cameras.
2. Implemented a robust background subtraction method suitable for dynamic lighting and multiple motion conditions in aquatic environments.
3. Composed a feature set based on swimmer shape, direction of motion, and velocity, which is essential for distinguishing between normal and distressed behaviors.
4. Constructed a Finite State Machine (FSM) that utilizes the sequential behavior of swimmers to identify and classify real-time drowning scenarios.
5. Employed Kalman filtering techniques and contouring to track multiple swimmers across stitched video feeds obtained from overhead cameras.
6. Integrated an automated rescue trigger mechanism that continuously maps swimmer coordinates and activates rescue actions based on the severity levels of drowning.
7. Validated the proposed system using multiple simulated drowning scenarios and achieved strong agreement with expert lifeguard assessments.

2. Related work

Human detection, surveillance of objects throughout the video stream, and motion inference are common components of automatic visual monitoring systems for human movement tracking [7]. The human is often seen as the video frame's foreground. As a result, it may be detected using the background subtraction method. For the sake of speed, memory use, and accuracy, a variety of background removal approaches have been examined in detail [20], [25]. Preprocessing and background modeling, including foreground identification and validation, have been covered in a comprehensive review [20]. Background subtraction approaches for visible data, unconventional data (e.g. audio or infrared), and their integration are discussed in detail in [22]. Subtracting the static backdrop and video frame from the current video frame is the first step in [11], [23]. Dynamic foreground and background pixels are used to describe the location of pixels in a moving image.

On top of that, the Markov Random Field model is being used to deduce a greater degree of coherence across the labels. Local patterns in pixels may be modeled using kernel density estimate approaches. For removing the dynamic background, multi-modal background models and multiscale fusion approaches are created [25]. Type-2 fuzzy MoG models simulate dynamic backgrounds such as flowing water and waving trees [26], [27]. A blend of Gaussian distributions has been used to describe swimming pool backgrounds [24], [28]. A video surveillance program capable of identifying drowning accidents has been presented in [7]. Block-based background modeling and hysteresis thresholding methods have been introduced for swimmer detection [29], [30]. Hidden Markov Models (HMMs) are used to identify crises.

Recent advancements in deep learning-based drowning detection systems have demonstrated promising performance [1], [3], [4], [15]. Real-time near-drowning detection using Mask R-CNN and YOLO frameworks has been investigated in [14] ,[22]. Transformer-based underwater drowning detection approaches have also been introduced [31]. AI-enabled surveillance systems for beaches and outdoor aquatic environments have been proposed [5], [8] , [16] . Swimming activity classification using machine learning has been studied in [6]. Underwater detection techniques using CNNs, YOLO variants, and feature pyramid networks have been explored in [34]–[36]. Deep residual learning architectures that enhance detection robustness are widely adopted in computer vision systems. Optical flow-based motion estimation techniques, including classical formulations, remain fundamental in dynamic scene modeling.

Motion-based drowning indicators such as velocity reduction and behavioral anomalies are consistent with observations reported in [18], [25]. Advanced video-based drowning detection systems using convolutional autoencoders and improved feature extraction mechanisms are presented in [4]. Occupancy analysis and swimmer monitoring using low-quality video streams are explored in [12], [13]. Wearable and sensor-based drowning detection approaches using pressure and inertial sensors have also been investigated. Audio-based distress signal detection systems complement visual monitoring techniques [33].

Forensic drowning diagnosis using deep neural networks for diatom detection has been proposed in [17]. Postmortem CT-based drowning diagnosis frameworks are discussed in [26]. Rip current detection using lightweight deep learning architectures contributes to drowning risk mitigation in open water scenarios [32], [35]. Background modeling approaches such as W4 real-time surveillance systems are discussed in [27] –[30]. Kalman filtering remains a foundational approach for object tracking in dynamic environments.

These studies collectively demonstrate the evolution from traditional background subtraction techniques to modern deep learning and multi-modal drowning detection systems. However, challenges remain in robust detection under highly dynamic aquatic environments, motivating the development of the proposed framework.

3. Problem statement

Development of a vision-based system for possible early detection of drowning incidents by using only multiple overhead cameras. Vision-based strategies are found to be more generic and independent of data, up to a certain threshold. These vision-based techniques may face several challenges in building an automatic drowning system because of aquatic environments. we use Gaussian distribution models to evaluate the entire pool area which is under observation, rather than any pixel in the background, to handle the huge changes in pixels of background owing to oscillations of water and to take advantage of visual consistency in swimming pools. With this method, the background model may be stored in less RAM, which makes it simpler to update.

In this situation, we are looking for human gestures that may be indicative of drowning and hence need further investigation. Research into human motion analysis has been extensive [23], but few studies have examined how people react to potentially harmful circumstances, such as drowning. The fundamental problem is that there are not many instances of persons in danger exhibiting these abnormal movements. Using synthetic agents that replicate human movements and then training a behavioral model on the synthetic data, the authors [35] address the issue of insufficient training data when tested on a few films of genuine pedestrian scenarios, the algorithm produced encouraging results. For example, in [36], the authors perform research to create approaches for detecting human emotional states like pleasure and sorrow from four physiological indicators. A single subject is used in their investigations since each person's perception of the same emotion may be different, thus they use descriptive criteria to acquire consistent physiological data.

4. Methodology

We suggest a computer assisted process for detecting drowning incidents in swimming pools in this paper. In the first phase (swimmer detection module), samples/frames of i) people swimming in pools in normal circumstances and ii) people drowning in pools are collected. Swimmers are detected and separated as foreground objects from the swimming pool background model. Swimmer tracking is used to discover the features of an individual swimmer and the preset characteristics are derived using the detector and tracker algorithm. These characteristics are utilized to infer a swimmer's spatial and temporal information. As a result, the features incorporate temporal information, making feature reduction an ineffective way to minimize the feature set. Furthermore, the derived features only comprise orientation and behavioral data associated with a single swimmer, and missing any information geographically or temporally might degrade inference performance.

In the next phase, we will obtain high-quality real-time video of a swimming pool. The video will be divided into samples/frames. The relevant features, as mentioned in the first phase, will be extracted from the frames. The feature set will be used with the training model to detect drowning accidents. The accuracy of the proposed workflow will be evaluated using state-of-the-art objective evaluation measures. The experimental results will also be compared with other recently developed techniques. The model will be implemented and the results will be obtained in real-time on real scenarios [28].

The proposed model will help reduce the casualties that may happen due to drowning accidents at swimming pools. The model will also help in providing emergency rescue to the victims of such incidents. This study proposes a stereo-based rescue tracking system for a drowning individual in a swimming pool.

Four cameras of good resolution are mounted on the corners of the swimming pool to identify the individual. The four cameras' images are captured constantly after the photos are obtained, the first stage in processing is to assess their quality. If the picture quality was acceptable, it was processed further. However, if the picture quality was poor, the algorithms would increase the image quality. Since the an acquired picture is 24-bit RGB, first, it can be converted to grayscale. Diverse filtering methods would be used to remove distortions and artifacts created during capture and enhancement, allowing the recovered picture to resemble the improved blank image. The grayscale picture is then transformed into a binary image using a threshold method. This means that, if the item drowned, numerous photos were analyzed and If the object's pattern changed fast, it was considered as a drowning, and a command was issued to the rescue control center.

From the current work, it is feasible to employ a small number of people's data from a simulation, and the approach used to gather and analyze the data should be extended so that it may subsequently be used to construct a comprehensive system, which can then be used to infer human emotion or behavior. A similar idea was used to create and test the suggested method, which was based on video data collected from swimmers who copied the actions of drowning swimmers while following the instructions of a trained lifeguard who had seen a documentary movie about drowning cases.

The challenges, we addressed are listed below:

1. Detection of swimmers wearing swimming dresses of any colour
2. Tracking of all the swimmers
3. Characteristics needed to analyze and characterize swimmer behavior
4. Defining rules to mark an incident as a drowning person
5. When analyzing an incident, provide temporal data for some time.
6. How can the event be detected in its early stages?

The proposed method is based on predetermined norms from the professional water industry. According to existing understanding and study suggestions, is largely dependent on swimmer behavior [23]. These drowning incidents can be detected by inspecting the struggle of the swimmer in the water and these behavioral signs, referred as IDR in [24], are universal responses of drowning swimmers to the actual or perceived feeling of suffocation in water. Depending on the nature of the struggle, drowning swimmers can be generally categorized into two types.

1. Actively drowning swimmers
2. Passively drowning swimmers

A passive drowning swimmer normally slips underwater without much struggle, whereas an active drowning swimmer struggles before sinking to the bottom of a swimming pool. Thus, a sudden lack of movement can be used to detect passive drowning swimmers. However, no single criterion can reliably and quickly identify an active drowning swimmer. The motion characteristics of aggressive drowning swimmers as follows.

1. To support themselves, they automatically stretch their arms laterally.
2. They lack voluntary control of their limbs and struggle to stay afloat for 20-60 seconds.
3. Their bodies stay upright in water and cannot move horizontally or laterally. These motion features are employed by lifeguards nowadays to detect drowning swimmers. So, we used these motion features to assess the swimmers' condition.

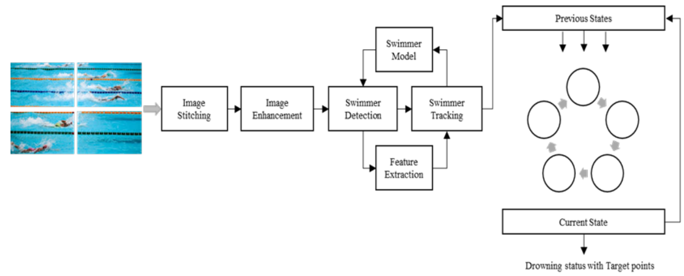

Figure 1: Flowchart diagram of the proposed model.

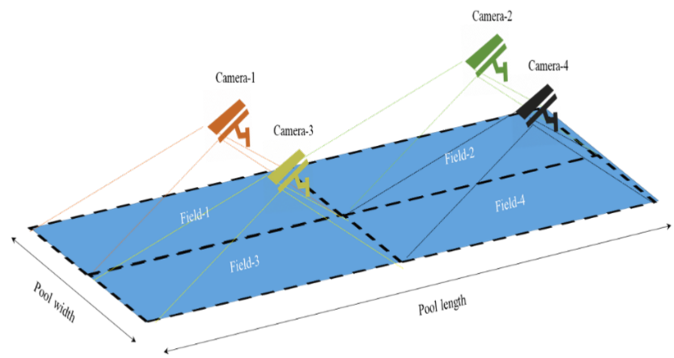

Figure 2: Camera field and region of interest.

4.1. Pre-processing

Pre-processing is the basic step required to form the input streams such that further processing can be applied to the pre-processed images. Four cameras are installed on the pool with the configurations shown in Figure. 2. Where four cameras are mounted over a pool in a way, such that all the cameras are supposed to cover a non-overlapping region of the pool. Time-synched frames obtained from all the cameras are stitched together to form a single frame. Obtained stitched frames are converted into HSV format as the HSV format is proven the most effective format to segment out the foreground and background. RGB to HSV transformation algorithm was implemented, where input (RGB) and output (HSV) frame.

4.2. Background extraction

A single Gaussian would be enough to segment out background and foreground under specific lighting conditions and it models the pixel's values while accounting for acquisition noise. On the other hand, if the lighting has variation over time, a single adaptive Gaussian model would be enough to segment out the foreground and background. In general, multiple variations in the lighting of a particular pixel lead to the use of the multiple adaptive Gaussian. Hence, in aquatic scenarios, lighting conditions vary per pixel in terms of reflections and moving water surface, so we used a mixture of adaptive Gaussian for process approximation.

5. Results and Discussions

Gaussian parameters are updated and evaluated using a simple heuristic and considered as a part of the background

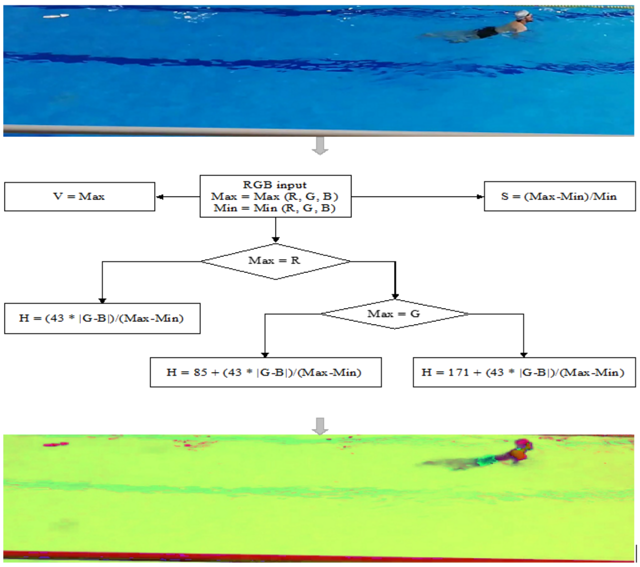

Figure 3: Input RGB frames and corresponding HSV-converted frames.

process. Gaussians are grouped using connected components if pixel values do not match one of the background pixels. These connected components are tracked over the temporal frames using a multiple-hypothesis tracker. A general architecture of the adaptive GMM model is shown in Figure 3. and the following sections are devoted to the operation of the adaptive GM.

Values of particular pixels over a temporal frame range are defined as pixel process and these are scalar for non-RGB images. At any time stamp, the known history of a pixel can be formulated as (1):

$$\{X_1, \ldots, X_t\} = \{I(x_0, y_0, i) : 1 \leq i \leq t\} \tag{1}$$

In (1), I is the sequence of images.

Each pixel value depicts a radiance measure towards the direction of the first object intersected by the optical ray of the pixel. This measure remains constant of the background lighting remains unchanged. A lighting variations, moving objects, and scene changes can be seen in most of the scenes which is the case in aquatic environments. Gaussian must track the changes in lighting conditions. Further, if the moving object contains consistent colors, the moving object is supposed to produce more variance than a static object.

The recently maintained history of each pixel, $\{X_1, \ldots, X_t\}$ can be modeled as the K Gaussian distributions. Observational probability of the current pixel is (2):

$$P(X_t) = \sum_{i=1}^{K} \omega_{i,t}\, \eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \tag{2}$$

In (2), $\omega_{i,t}$ is the weight estimation in terms of the data portion counted for the ith Gaussian, K denotes the number of distributions, and $\mu_{i,t}$ represents the mean of the mixture at time t.

$\Sigma_{i,t}$ denotes the covariance matrix of the ith mixture at time t, and $\eta(\cdot)$ represents the Gaussian probability density function.

The probability density function Gaussian mixture

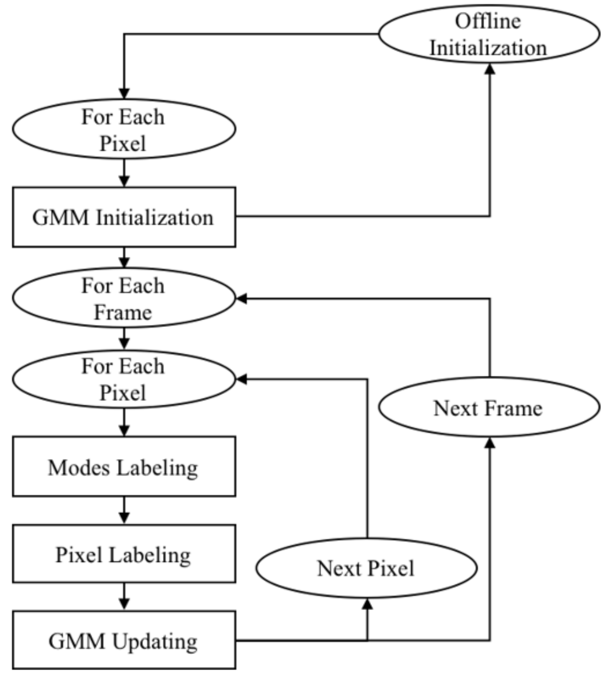

Figure 4: Adaptive Gaussian Mixture Model (GMM) for background and foreground separation.

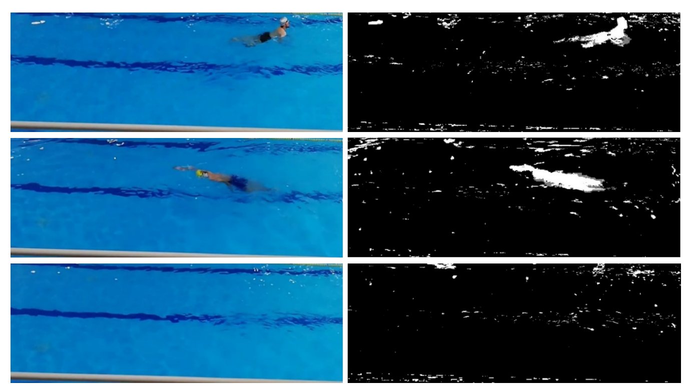

Figure 5: Portions as foreground.

model can be formulated as follows (3).

$$\eta(X, \mu, \Sigma) = \frac{1}{(2\pi)^{n/2}\,|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(X_t - \mu_t)^T \Sigma^{-1} (X_t - \mu_t)\right) \tag{3}$$

We empirically selected the value of K. So the pixels are characterized by a Gaussian mixture model such that a new pixel value is represented by one of the major Gaussian components and used in model update. Every new pixel is checked to match the Gaussian mixtures and a match is threshold at the distance of 2.5, standard deviation which is selected empirically.

We may use the approach mentioned above to detect foreground pixels in each new frame while also updating the process description for each pixel. A two-pass, linked components method may then partition these annotated foreground pixels into areas. Moving areas may be defined not only by their location, but also by their size, moments, and other shape information since this approach is useful in identifying the whole moving item. These traits may be

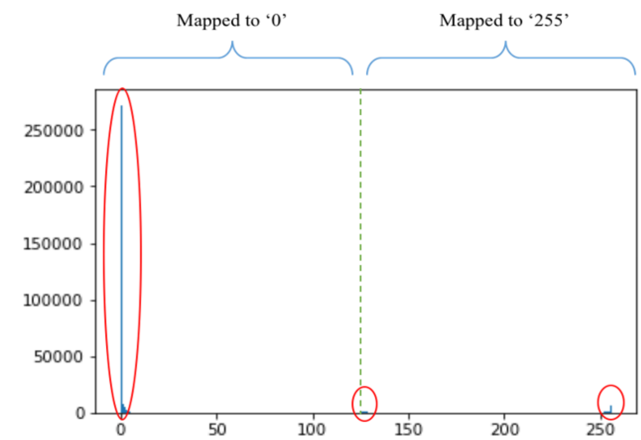

Figure 6: Thresholding algorithm.

important not just for further processing and categorization, but also for tracking.

Input frames and corresponding segmented output is shown in Figure 5. It can be seen that the small variation in water due to occlusion or variation in lighting condition segmented the small

5.1. Thresholding

The GMM returns the detected swimmers separated from the background. It results from a grayscale mask such that the swimmers are masked with '0' values, the background is masked with '255' value, and a value of '127' is obtained against the shadows or the water splashes. Hence, the swimmer's movement produces water splashes around his upper limb and on the traces. This information can be incorporated into swimmer masks. We applied Otsu thresholding such that it connected the water splashes with the human as a prominent feature.

Otsu method generates a histogram of an image and divides the under-consideration histogram into two classes by observing within-class variance and between-class as shown in Figure 6. A threshold value (marked as the green dotted line in the graph) is selected to consider the water splashes as the swimmer feature rather than the background—furthermore, the input and resultant output of Otsu.

Background and foreground segmentation results. Left column: input camera stream, Right column: corresponding result from foregrounds.

5.2. Morphology

The obtained thresholding results may contain small patches of background marked as foreground. This wrong classification of pixels mainly occurs due to small variations in lighting conditions and movements of water on the surface along with the guidelines. To address this problem, we applied opening and closing functions iteratively and the number of iterations and sequence is selected empirically. The opening function reduces the small noise (the small foreground patches) while the closing function fills the missing values. In that manner, we obtained binary images without having any misclassified foreground and background. Morphological results are shown in Figure 7.

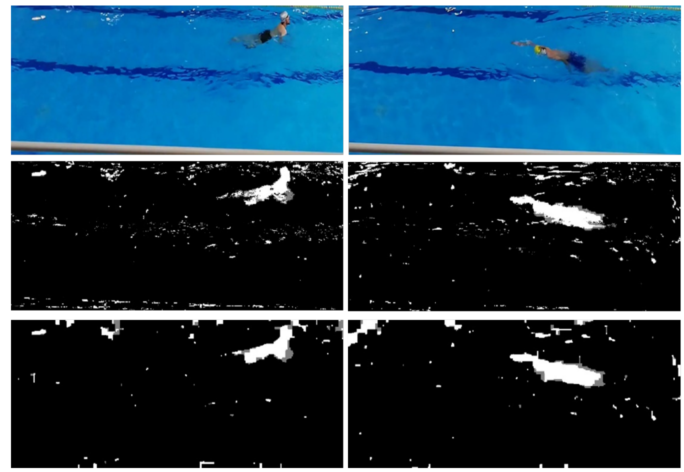

Figure 7: Thresholding results obtained on segmented masks as Row 1: input camera stream, Row 2: segmentation results, and Row 3: thresholding results.

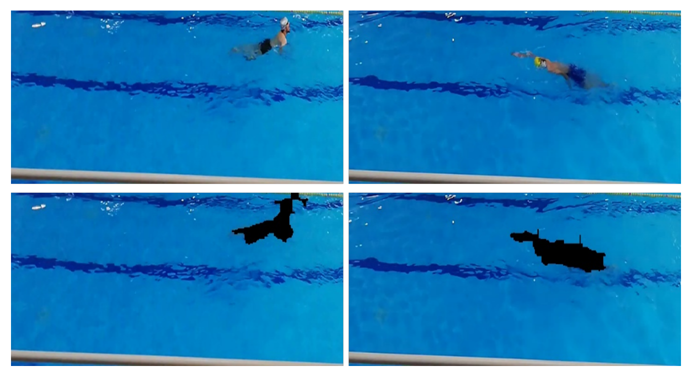

Figure 8: Contours obtained from the contouring algorithm and mapped over the input camera stream.

5.3. Contouring

The obtained foreground and background masks in the form of a binary image are fed to a contouring function. Hence, many swimmers may appear in a predefined ROI, so dealing with each swimmer individually requires a unique identification of each swimmer. To do so, we applied contouring which distinguished the swimmer class from each other. To further reduce the noise and generalize the algorithm, a minimum threshold over contours is defined to distinguish any moving object other than a swimmer.

By having prior knowledge in terms of an average swimmer length in a swimming pool, the contours smaller than a threshold are removed which resulted in only the swimmer contours where each swimmer is identified as a separate identity as shown in Figure 8.

These contouring results are fed to the tracking algorithm to track each individual swimmer and analyze its swimming pattern.

5.4. Swimmer tracking

In recent years, there has been a lot of interest in video segmentation, estimate, and tracking of semantic objects. Surveillance, sports coverage, video annotations, and traffic control systems all have moving object tracking as a major difficulty. Moving items in the background, on the other hand, alters dynamically, which might be difficult to manage. To recognize and track moving things in video analysis, we need to know the features of moving objects such as colors, textures, forms, and so on. In the actual world, there are several video scenarios, such as camera lenses. Multiple moving objects, stiff or non-rigid objects, occluding objects, one or more cameras, completely automated or semi-automatic semantic object tracking, and so on. Based on the above explanation, we believe that monitoring mobile targets will provide the following three challenges. In the original moving object segmentation problem, the method was specified with the help of the user. KALMAN prediction method has been summarized below. Notations and variables used in the algorithm have also been summarized.

$$X(k|k-1) = AX(k-1|k-1) + BU(k) \tag{4}$$

$$P(k|k-1) = AP(k-1|k-1)A^T + Q \tag{5}$$

$$K_g(k) = P(k|k-1)H^T \left(HP(k|k-1)H^T + R\right)^{-1} \tag{6}$$

$$X(k|k) = X(k|k-1) + K_g(k)\left(Z(k) - HX(k|k-1)\right) \tag{7}$$

$$P(k|k) = \left(I - K_g(k)H\right)P(k|k-1) \tag{8}$$

In (4)-(8),

1. $X(k|k-1)$ is the predicted value of the current time state based on the previous moment of the current time.
2. $X(k-1|k-1)$ status value at the previous moment of the current moment..
3. $U(k)$ is the amount of system control at the current moment, that is, the system input, none is 0.
4. A: state transfer matrix.
5. B: status input matrix.
6. $P(k|k-1)$ calculates the predicted value of the current time covariance based on the covariance of the previous moment.
7. $P(k-1|k-1)$ covariance optimal result at the previous moment.
8. Q system process noise covariance.
9. B) system process noise equation (3). calculated covariance of Kalman gain.
10. $K_g(k)$ current moment Kalman gain, indicating the variance of the estimated amount and the variance of the measured amount.
11. H system measurement matrix.
12. R measurement noise covariance matrix.
13. C) equation (4)(5) update calculation
14. $X(k|k)$ current time optimal value estimate.

The target detection model is shown in Figure 9. Here it must be noted that based on the target segmentation the position and velocity of the target are estimated. Optimization algorithms would be applied for the optimized tracking of targets

Motion vectors recomputed over each swimmer and the movement of its corresponding limbs with motion direction are also tracked over time. The obtained motion vectors are used to monitor the swimmer's velocity, motion direction, speed, and other information contributing to rules and features.

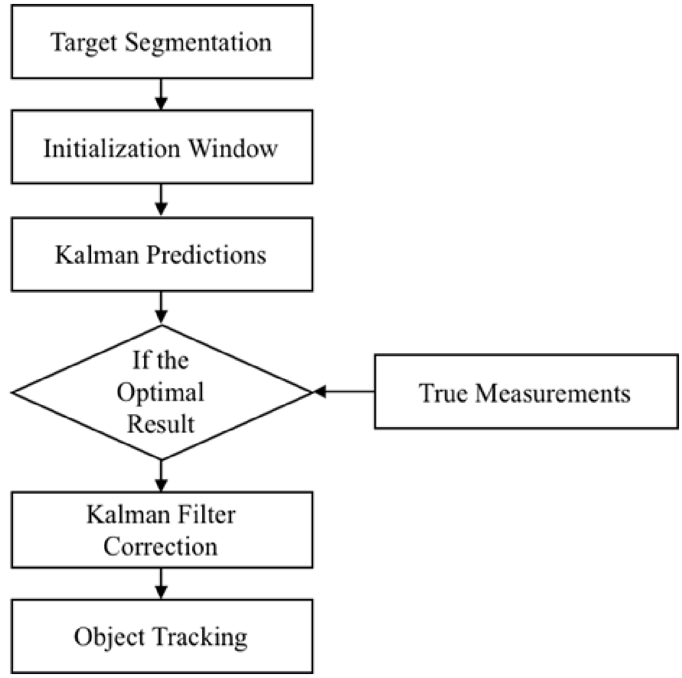

Figure 9: Target detection and tracking model

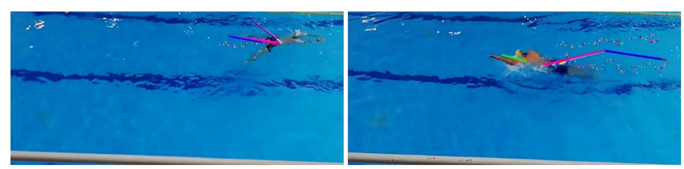

Figure 10: Tracked swimmers with motion vectors associated with their corresponding limbs.

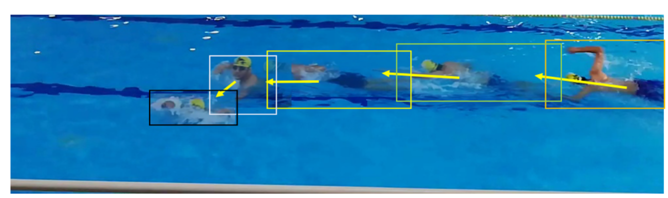

Figure 11: Object tracking results are obtained from the Kalman filter where the frames are sampled for a specific constant period.

5.5. Feature Extraction

From each detected swimmer, several features are obtained and passed to the inference module to check over a set of predefined rules for swimmer condition evaluation. Non-stationarity of aquatic environment requires a combination of features that must be robust enough to handle movements of other objects and lighting conditions.

Motion vector commutation is shown in the Figure. 10. where each color of the motion vector corresponds to a unique limb. Tracked objects over a specific period and sampled can be seen in the Figure. 11. where bounding boxes over the object capture the entire segmented body and track in each frame

To obtain a robust feature set, swimmer movement, and orientation details can be combined. List of the features used in this research are:

- Swimmer shape
- Motion direction

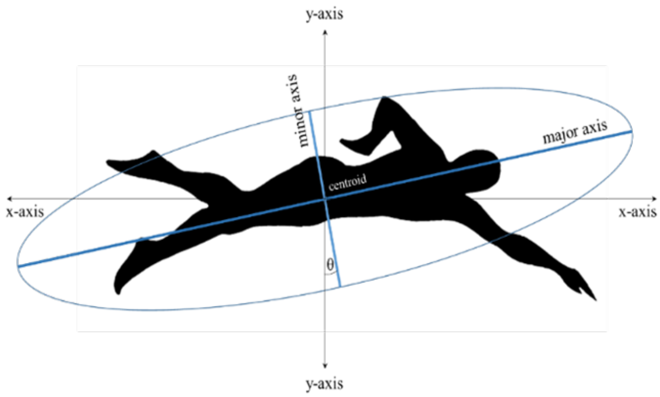

Figure 12: Swimmer shape and orientation geometry

- Swimmer velocity

Detail of each feature is given in the following sections.

5.6. Swimmer shape

The swimmer's shape and orientation is a major features that can be detected by fitting a predefined shape over the swimmer. Convex hull, rectangular bounding box, and polygon have also been tried and a rectangle bounding box is found to be the most effective shape in our scenario. Hence the shape fitting depends on the geometry of the camera and view of the region of interest. We focused on the major and minor axis of the object and considered the length of the swimmer as the major axis and the width of the swimmer as the minor axis.

To fit the feature shape, a centroid of the object body is calculated which is based on the area a swimmer covers and the centroid acts as the crossing point of the major and minor axis. Figure.12 shows the shape fitting over a swimmer and its orientation in terms of major and minor axis concerning the global x and y-axis.

The ratio between the major and minor axis is used as a feature such that it is observed that when a swimmer is found to be drowning, its shape transforms such that the major axis reduces as compared to the minor axis and ellipse or the fitted shape tends to reduce towards a circle or rectangle. In such scenarios, the angle between the global y-axis and minor axis tends to increase which is another major feature to be considered. In summary, the Swimmer shape resulted from the following features:

- The ratio between the major and minor axis
- The angle between the minor axis and the global y-axis

The ratio between the major and minor axis can be computed as (9).

$$R = \sqrt{\frac{I_{\max}}{I_{\min}}} \tag{9}$$

In (9), $I_{\max}$ and $I_{\min}$ denote the largest and smallest moments of inertia, respectively, which can be calculated as follows (10)-(11):

$$I_{\max} = \sum_x \sum_y [(y - y_c)\cos\theta - (x - x_c)\sin\theta]^2 \tag{10}$$

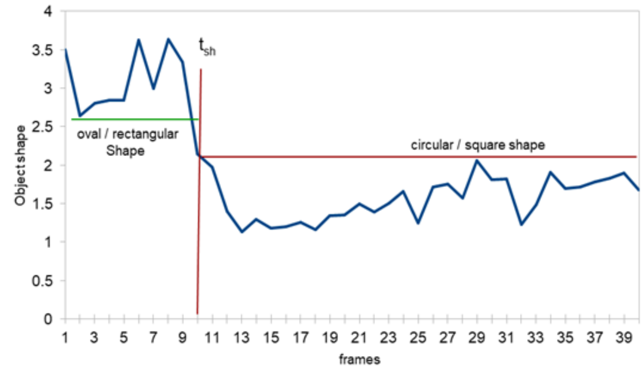

Figure 13: Swimmer orientation and shape where tsh is the shape/orientation threshold

$$I_{\min} = \sum_x \sum_y [(y - y_c)\sin\theta + (x - x_c)\cos\theta]^2 \tag{11}$$

In (11), x and y denote the segmented pixel coordinates belonging to a particular swimmer, with $\{x, y\} \in \mathbb{R}$. The terms x_c and y_c represent the centroid coordinates of the swimmer object, which are computed by averaging the pixel locations along the x and y axes, respectively.

$$x_c = \frac{1}{N} \sum_x \sum_y x \tag{12}$$

$$y_c = \frac{1}{N} \sum_x \sum_y y \tag{13}$$

The angle between the minor axis and the global y-axis can be calculated as (14).

$$\theta = \frac{1}{2\tan^{-1}\left(\frac{2\mu_{1,1}}{\mu_{2,0}} - \mu_{0,2}\right)} \tag{14}$$

The ratio between the minor axis and global y-axis is measured over a stream of input frames and examined if the ratio reduces over time for a certain period. The reduction in R shows that the shape of a swimmer tends to be circular or square. Further, if the angle increases and remains greater than a certain value for a predefined period of time, this also shows that the swimmers' orientation is changed from horizontal to vertical. The feature set obtained from the swimmer shape is summarized in (15).

$$F_o = \{\theta_{t_0 - t},\, R_{t_0 - t}\} \tag{15}$$

In (15), $t_0 - t$ is the period in which a swimmer's orientation is observed. Figure 13 depicts the swimmer's shape over some time. The temporal difference between each sequential frame is the same and marked with $t_1, t_2, \ldots, t_3$. It can be seen that the shape of the swimmer changes, as highlighted with ovals.

Swimmer tracking body shape measurements in terms of mapped oval as shown in Figure 14.

5.7. Motion direction

From the swimmer tracking algorithm, the motion vector of the swimmer is observed and continuously traced

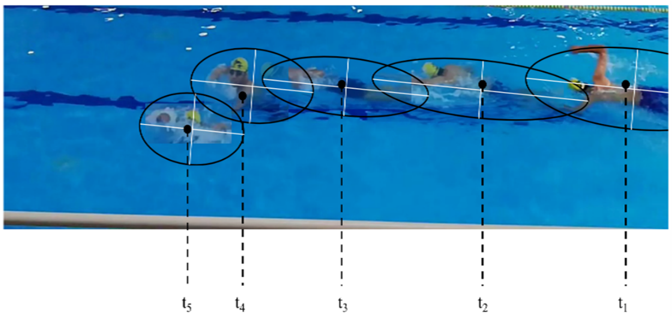

Figure 14: Swimmer tracking body shape measurements in terms of the mapped oval

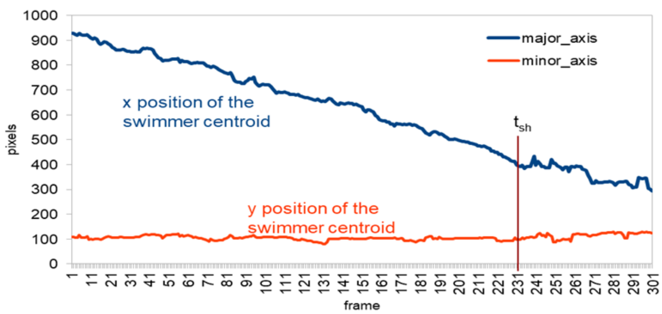

Figure 15: Swimmer motion direction analysis along both the x and y-axis.

while retaining the previous results in the given region of interest. If the swimmer moves along the major x-axis, its orientation is observed over some time. Once a swimmer diverges from its direction or its moving vector changes its direction in ± y-axis, the value of deviation infers that the swimmer needs an emergency or planning to quit the lap. The motion direction is observed along with the orientation feature and can be referred to as (16).

$$F_m = \{M_{xt_0-t},\ M_{yt_0-t}\} \tag{16}$$

Furthermore, the visual interpretation of the motion direction of an object over some time is shown in Figure 15. The vectors provide two types of information:

- Motion direction
- Motion intensity

These features can be used to identify the state of a swimmer. Motion intensity does not have any direct relation with the drowning state so we dropped this information.

5.8. Swimmer velocity

Swimmer velocity is another important parameter that depicts the swimming features. As a general practice, during a drowning incident, the speed of a swimmer reduces along with the orientation. Measuring the velocity of a swimmer results from a strong feature. If velocity reduces over time while the swimmer is not at the start or end of a lap, a drowning event may trigger. We incorporated swimmer velocity as a sub-feature which can be represented as (17).

$$F_v = \{v_{xt_0-t},\ v_{yt_0-t}\} \tag{17}$$

The swimmer's velocity is computed over a while and observed when a swimmer switches from normal swimming

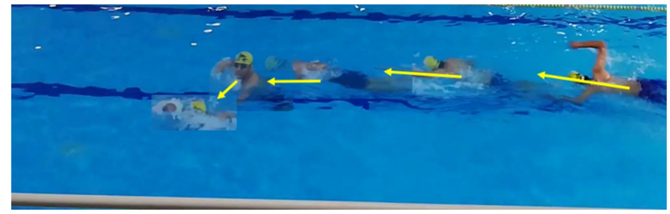

Figure 16: Motion vectors over tracked objects where the length of each vector shows the motion intensity.

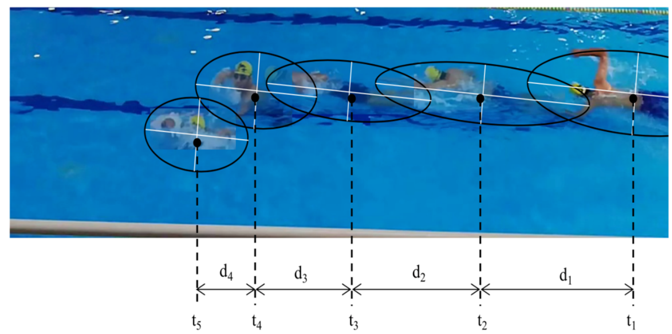

Figure 17: Swimmer velocity over a period of time.

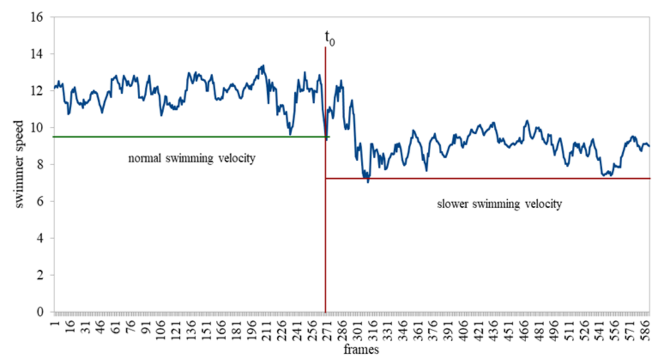

Figure 18: Swimmer velocity in normal and drowning conditions with t_0 is the threshold point.

to a drowning event which is shown in Figure 17. A threshold value t0 is defined as the switching time stamp and monitored at each frame. The reduction in swimmer velocity is used as a feature along with the other features to map the rules and states of the finite state machine model. Quantitative measures of swimming velocity are shown in Figure 16.

By combining all the features, a final feature set is obtained on which rules are defined to apply to a finite state machine classifier. This final feature set can be formulated as (18).

$$F = (F_o, F_m, F_v) \tag{18}$$

$$F = (\theta_{t_0-t}, R_{t_0-t}, Mx_{t_0-t}, My_{t_0-t}, vx_{t_0-t}, vy_{t_0-t}) \tag{19}$$

5.9. Event inference

The event inference module is designed to detect an event based on predefined rules. These rules are defined on the feature set by combining different scenarios that lead to an event. The usual pattern which can be analyzed using the defined feature set is listed in the following sections. We defined four kinds of rules on the features obtained from the feature extraction stage to trigger events and based on these rules, drowning incidents are classified. All four rules can be defined as Rule I to Rule IV. These rules are defined based on normal practice in drowning events such that occurrences of one or a combination of these rules lead to a drowning state. The detail of each rule is discussed in the following sections.

1. Rule I: slow movement
2. Rule II: vertical body posture
3. Rule III: fast limb movements
4. Rule IV: unconscious state

5.9.1. Rule I (Slow movement):

In normal practice, swimmers follow a near-constant speed in swimming pools and any decline in swimming speed may lead to satisfying Rule I which depicts that a swimmer is facing a problem and this information incorporated with other rules may infer a better understanding of the swimmer's condition.

5.9.2. Rule II (Vertical body posture):

Body posture is an important feature to be counted for a drowning state. Normally, simmers' body posture remains horizontal to the ground, and fitting an ellipse or rectangle over the segmented body returns major and minor axes. The major axis spans from head to legs whereas the minor axis spans over the body width. If the minor axis reduces as compared to the major axis, the fitted ellipse or rectangle turns into a circular or square shape. This information is used to detect the swimmer's position in a swimming pool. If the ratio between the major and minor axes reduces to a certain threshold value, the event is triggered.

5.9.3. Rule III (Fast limb movements):

Limb movements are another major feature that can be mapped to a rule such that if a swimmer moves his limbs faster with reduction in the swimmer's speed leads to an event. To detect a change in limb movements, swimmers are tracked and each moving limb is also tracked as a separate identity linked to a particular swimmer. Motion vector and motion speed of limbs can provide the limb movement information. We averaged all the limb movements to check the movement speed.

5.9.4. Rule IV (Unconscious state):

It is found that after moving limbs faster than a normal state while leading to a drowning event, swimmers may face unconsciousness. Limbs movement speed and the span of fast movement over time can be used to measure the consciousness of a swimmer. This rule combined with other rules returns a measure of drowning state.

To differentiate the swimmer conditions, we utilized a finite state machine by integrating combinations of rules defined in the previous section. Swimmer conditions can be categorized into three states:

1. Normal
2. Possible drowning
3. Drowning
4. Unconsciousness

Table 1: Transition state and rule mapping.

Current State	**Next State**	**Transition Criteria**
Normal	Possible Drowning	Satisfy Rules I, II
Possible Drowning	Normal	Not satisfy Rules I, II, III, IV
	Drowning	Satisfy Rules I, II, III
Drowning	Normal	Not satisfy Rules I, II, III
	Possible Drowning	Not satisfy Rule III
Unconscious	Unconscious	Satisfy Rules I, II, III, IV
	Drowning	Not satisfy Rule IV

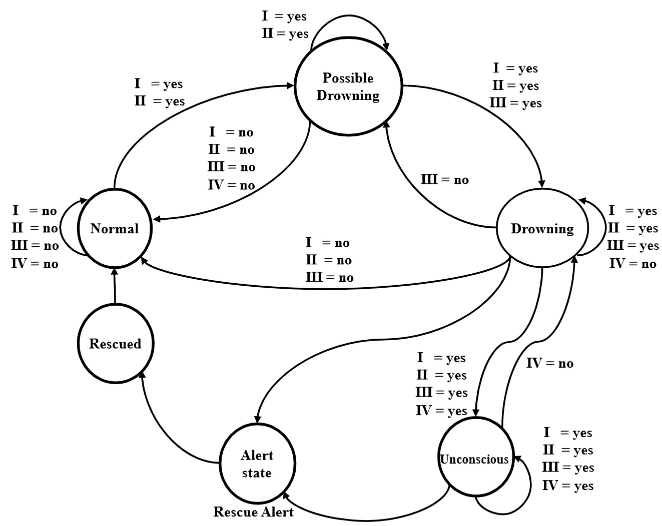

Figure 19: Finite state machine model for the proposed methodology.

These conditions are mapped over the defined rules and several combinations leading to states are defined. The mapping of rules and drowning conditions with states of the FSM model is summarized in Table.1.

Cases mapped on the combination of the defined rules are used to implement the finite state machine model. The FSM model is shown in Figure 20. Five states are maintained which include: normal, possible drowning, drowning, alert, and rescued state. These states are defined by the combination of different rules.

6. Temporal state transitions

There are four states of swimmers which may occur independently whereas two additional states are the systematic states to generate an alarm and restart the processing once the rescue operation is completed. In this project, we utilized a sequential change detection algorithm to measure the change in the underlying mapped features which leads to inferring the swimmer condition. The FSM model is shown in Figure. 20. It can be seen that there are four states (normal, possible drowning, drowning, and unconscious) specific to the swimming conditions whereas two

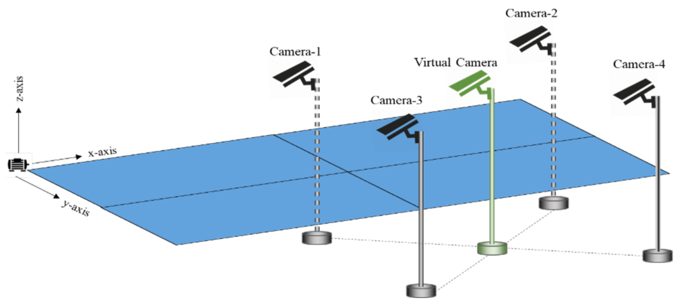

Figure 20: Camera installation and field of view with the final composite view (central green camera).

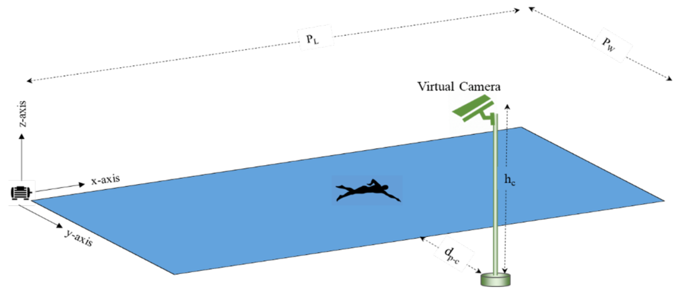

Figure 21: Illustration of pixel coordinates to distance mapping.

states (alert state and rescued state) are for system requirements. Every state has a piece of temporal information or depends on a certain definition over time. These time durations are selected empirically.

7. Rescue commands

Capturing the swimming area using four cameras without having any overlap region requires the election of the region of interest which is part of preprocessing. Once a composite (stitched) stream from all four cameras is generated, feature detection and event classification modules are executed on each frame. At the time of event occurrence, the proposed model results from the state of the swimmer and its location in the predefined region of interest in terms of the x, y, and x z axes. A hardware module consisting of three motors is installed at static location of the swimming pool which moves the rescue object towards the swimmer.

A mapping is required to translate the 2D-pixel location of the swimmer into the distance and height of the swimming pool. The composite image obtained from all four camera streams shows the central view of all cameras. These phenomena are shown in Figure 21.

where a virtual camera is displayed as the resultant stream after applying stitching to all four camera streams. Three motors are installed at the top left corner of the swimming pool where each motor can control the rescue object with two degrees of freedom. To generate commands with the physical location of the drowning swimmer, mapping between the detected position in the image and the actual location of the swimmer in a swimming pool is required. To address this problem, a set of parameters is defined which solve the camera geometry and pixel translation problem. Figure 21 illustrates the mapping and parameters required for mapping. Given a piece of prior information regarding pool length (P_L), pool width (P_W), camera height (h_c), and distance from the camera to pool boundary ($dp - c$), similarly the width and height of the image, a linear mapping can be placed. Pixel location to swimmer location transformation can be formulated as (20).

$$x_s, y_s, z_s = \frac{P_L}{I_w}, \frac{P_W}{I_H}, h_c - h_p \tag{20}$$

In (20), I_w and I_H are image width and height respectively, h_p is the height of the water surface from ground level if the camera height is measured from ground level. As a final result, the model results from the position of the swimmer if the swimmer is in a drowning situation.

The severity level of a drowning person is mapped to the drowning states. There are three drowning states which corresponds to the respective drowning level. Near drowning is stratified as level 1, the drowning state is mapped to level 2 and the unconsciousness state is presented by level 3. The proposed model passes the drowning severity level and the location of the drowning person.

8. Conclusion

This paper presents a novel vision based framework for the early detection of the drowning incidents in aquatic environments using only overhead RGB cameras without requiring the wearable sensors or any other underwater equipment. The poposed strategy is developed in three sections.1st a visual processing module which detects and also tracks the swimmers in real time. 2nd a behavioral feature extraction component evaluating the multiple motion patterns and posture indicators. 3rd an event inference model which is based on FSM for the classification of the swimmer behavior into the four different states which are slow movement, vertical body posture, fast limb movements and unconscious state. System achieved highly promising results through extensive evaluation and simulated drowning scenarios. It successfully detected the active and passive drowning patterns with detection reliability of in more than 90% different scenarios, also validated by the expert lifeguard judgements. Features like horizontal and vertical body postures, limb instability and velocity reduction proved to be effective in differentiating the distressing signals from the regular swimming bahavior. Moreover, the system demonstrated stable performance under the multiple lighting and background movement conditions due to the use of HSV color transformation and adaptive GMM. The designed system is able to successfully identify swimmer's coordinates and stimulate a time response thus confirming the practical applicability of the system for teal worls deployment. Briefly this study introduces a reliable, low cost and non invasive solution for the drowning detection addressing many challenges identified in traditional systems. By combining real time tracking, motion analysis and FSM based behavior classification the proposed framework offers a promising approach for enhanced swimming safety in diverse aquatic environments.

9. Future work

Future work will focus on the deployment of the system in real world aquatic environments to test its' robustness under the diverse conditios. Deep learning models can be integrated to enhance the behavior recognition and reduce reliance on the predefined rules. Moreover incorporating the depth sensors can present richer context for accurate detection. Also the system can be tested on expanded datasets to improve system's generalization and usability.

Declarations and ethical statements

Conflict of interest: The authors declare that there is no conflict of interest.
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Availability of Data and Materials: The data and/or materials that support the findings of this study are available from the corresponding author upon reasonable request.
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Author Contribution Statement: Muhammad Aftab Hayat implemented the model and prepared the manuscript. Shams ur Rehman assisted with data collection, preprocessing and manuscript formatting.

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