SwimTrack: Drowning Detection using RFIDs

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ABSTRACT

"RFID tags will be blocked by any material having similar characteristics as water". This was the primary motivation behind the SwimTrack concept.

SwimTrack is a solution that is potent to not only enable early warning of drowning, but also it can be used for several other purposes such as keeping track of the workout done by each individual or count the number of people that are located in each section of a swimming complex.

SwimTrack system consists of two RFID tags where each is attached to one of the individual swimmers and a couple of directional antennas that can be ideally placed on the ceiling of the swimming pool and a single RFID tag reader that reads the tags periodically and records the logs in a connected laptop.

The big picture of the project would be about analyzing the log files to extract the data related to each individual and infer about the duration each swimmer has been under water or above the surface of the water. Using such analyzed data, we propose that the system will be able to distinguish between swimming and drowning. Besides this, SwimTrack will be able to distinguish between the swimming styles.

1 INTRODUCTION

Statistics shows that the death toll related to drowning in Canada. It mentions a significant number of people (total of 466 by 2016) die due to lack of proper systems to prevent drowning. [2] Also there is only around 20 to 60 seconds time budget to rescue people while they are being drowning and during that time basically, the person is not submerged in the water and he is haphazardly coming up to the surface and going into the water. This phase is the golden phase during which the person should be rescued and other related works that rely on sonar systems, due to the fact that their system is based on detection of an object which is submerged in the water, might not be as accurate and as fast as ours. Thus there is a need for a robust, fast and low cost drowning detection system that can be implemented in any pool to prevent such loss.

RFID-based systems are very attractive as a means of communication for wireless tags in applications ranging from counting systems to localization systems. This is because of their low cost, small size and ease of maintenance since they do not require batteries in the tag side.

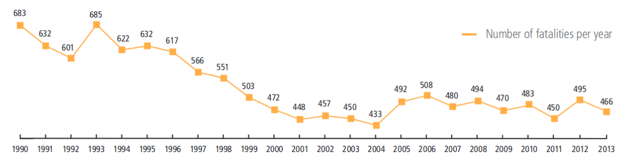

Figure 1: Number of Unintentional Water-Related Deaths in Canada, 1990-2013

Due to spread out use of commercial RFID-based systems, their readers, antennas and tags are widely accessible with proportional low price.

2 RELATED WORK

[5] The authors in this research present Sonar Based Drowning Monitor for early drowning detection in swimming pools. A US patent was filed by the authors in 2008 where transducers are utilised to capture images of the surface of the water body being monitored. Either a single transducer is used or a number of transducers are used to capture images depending on the water body. To distinguish between the people being monitored, sonar bar codes are attached to them and a series of images are captured for real time monitoring. These images are further transferred to a computer. The computer analyses these images to capture the behaviour, position and swimming patterns of the people being monitored to raises an alarm in case of an drowning event captured. The system is trained over the images captured over time to differentiate between different swimming patterns, treading patterns and drowning motion. The positional images captured are compared with the previous images to compare the changes in the position of the swimmer over fixed time intervals. If the swimmer is swimming normally then a periodic motion is recorded. In case the swimmer is still for a prolonged period or moves his/her hands around rapidly in a non-periodic manner might result in a potential drowning event. If a drowning event is detected, an alarm is raised for help. The invention is novel and does not require cameras to capture images of the swimmers in the swimming pool. This system involves a high setup cost since every swimming pool has a unique size and orientation. Placing the transducers at

the correct positions is important so that the entire pool can be covered. Moreover, it requires installing sonar devices on the floor of the pool that would potentially create problems for swimmers.

[3] The authors have highlighted the number of deaths caused due to drowning in the past and has been a significant reason behind the deaths. People die due to drowning mainly due to wrong swimming training or unavailability of life guards or help. Nearly 1.2 million people die every year because of drowning. There have previously been provisions and methods deployed to detect drowning in some countries but either due to the cost or difficulty in setting up, these systems haven't been deployed everywhere. The proposed system in this research monitors the rise and fall patterns of the heart rate and blood pressure of the person while drowning. When a person drowns, their heart beats faster in order to pump more oxygen in the blood. The person tries to keep his head above the water surface in order to breathe as much as possible. The swimmers are required to wear a wearable waterproof device that keeps monitoring the heart rate and blood pressure rate of the swimmer. The device is trained over the breathing patterns and in case a drowning behaviour is detected, the wearable device communicates with a server that raises an alarm for immediate help. The authors trained and tested their device on swimmers and non swimmers. The disadvantage here is that a person is required to buy an additional device that needs to be worn while swimming. These wearable devices are costly and moreover wouldn't be comfortable for everyone. Also, the authors could further research if their prototype could be incorporated smart watches that are generally waterproof and more and more people are buying them today.

[4] The authors present a computer vision approach for detecting drowning in swimming pools. The system uses a couple of cameras to capture images of the people swimming in the pool at fixed intervals of time. The cameras are placed at certain positions at the pool in order to cover the entire pool. The DEWS system has been trained over the different swimming patterns, treading patterns and drowning events using computer vision techniques. One challenge that the authors faced while developing DEWS was the presence of noise in the images captured that needed to be filtered out. A set of techniques including "background subtraction, denoising, data fusion and blob splitting" are proposed to filter out noise from the images. A model comprising of "data fusion and hidden Markov modelling" is used to detect distress or drowning event in a swimming pool. The system is trained over the images captured for distress that easily distinguishes between a swimming and drowning event. Various experiments were performed to test the validating of this approach and it was reported that the system worked well. One criteria that the authors did not consider was utilising the system in indoor and outdoor environments. The behaviours that the system has been trained on are distress, drowning, treading and various swimming styles. Cameras are expensive and the DEWS system requires a high setup cost. Moreover, every swimming pool has a different orientation and placing the cameras in order to cover the entire pool would come with a cost. Their are privacy concerns with cameras where the live recording of the images and be leaked by unethical sources. Therefore, there is a need of a more robust, cost-friendly and reliable drowning detection system.

[1] It is extremely difficult and takes a long time using professional divers and trained personnel to monitor water bodies for rescuing people who drown. There have been a number of deaths before help could reach them. The authors propose using using sensors that can be tracked for detecting drowning. RFIDs are used in this research to track the positions of the people. Over here, the system has been developed for open water bodies where a motor boat is tracked in case it goes out of range. The RFID readers are placed on the dangerous parts of the water bodies and the RFIDs are attached to the motor boats. The reader reads the RFID till the time it is in the vicinity of the reader and records the signal strength. Every tag has a unique ID that makes it easier to differentiate between the different boats. The boats also have a GPS fixed to monitor their position in the water bodies. When the boat goes beyond the range of the RFID reader an alarm is raised for help. This is not the correct approach for detection of drowning and the proposed is rather a range detection system. A person with the RFID tag who drowns might not be read by the RFID reader for a certain period till it is submerged in water and would be read once it is outside water. An alarm should be raised once the system verifies that a drowning event has occur ed instead of when the tag goes beyond the vicinity of the reader. Also, GPS wouldn't always give the accurate position of the person in an open water body and hence it would be difficult to localize the person.

3 RESEARCH METHODS

This section consists of two separate sorts of experiments. One conducted in the ICON lab, University of Waterloo to assess the feasibility of the whole idea of using a system like SwimTrack and the second is the real swimming experiments done in the PAC complex, University of Waterloo to ensure the systems functionality in action. The latter is discussed in the Experimental Setup section and the other is the one which is about to be elaborated here.

Figure 2: RFID tags when the whole antenna is touching the skin of the human body

Effect of being wet on the tags

First, we tried conducting a couple of experiments with bare RFID tags that were wet. The results were frustrating. If the tag was placed any further than around 1 meter away from the directional antenna, it was not readable any more.

So, we tried isolating the tag to prevent the actual physical antenna becoming wet and tried it in different distances from the antenna. The result was that the tag was reflecting as soon as it was coming out of the water with the maximum range of 4.5 m from the antenna.

In conclusion, during the whole tests, tags that were isolated by electrical tape were used and attached to silicon bands to able the swimmer wear them all the time.

Effect of being attached to skin on the tags

We observed that while the RFID tags are touching the human body, the strength of the reflected signal from them will decrease steadily. Figure 2 shows the maximum range of the tag whose antenna is fully touching the skin while the antenna is reading by 32.5 db power.

Range and coverage of the antennas

In our experiments, we were using directional antennas that focus their beam toward a special direction. The range we could achieve using such antenna while transmitting by 32.5 db as it's power was around 8.5 meter line of sight. Figure 3 shows the maximum range of our antenna and the fact that the antenna will not work while there is no line of sight.

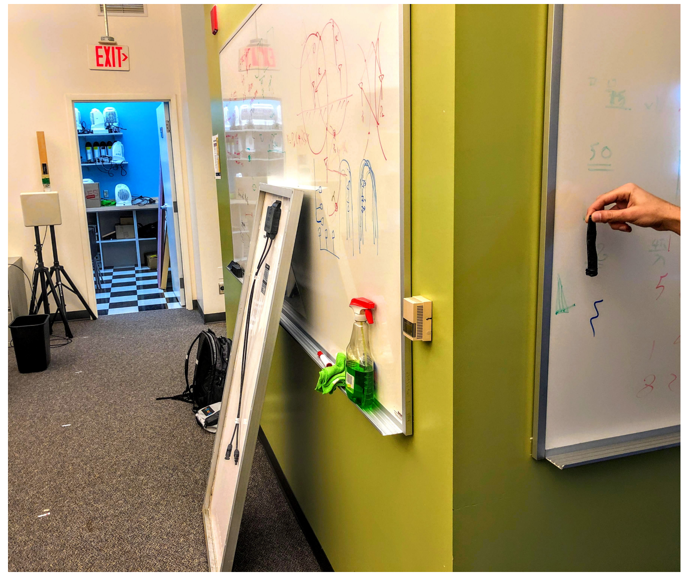

Figure 3: Range of the antenna used for the experiments

4 EXPERIMENTAL SETUP

The experiment was performed at the University of Waterloo campus swimming pool. The part of the pool where we performed our experiment had a size of approximately 10m by 15m and was 18 feet deep. The test subject performed a number of strokes to collect data including drowning motion. We used an Impinj RFID reader and an antenna as described above for reading the tags. We use two standard RFID tags, insulated them using plastic sheets and stuck them on the silicone wrist bands for easy wearability. The following image demonstrates our experimental setup:

If the tags are submerged in water, the reader does not record the reading of the tag and if they are outside water and in the vicinity of the antenna, then the reader detects them. To test the maximum range of the antenna, we requested the swimmer to keep the tags outside water and swim in perpendicular direction to the antenna. We recorded that after a distance of nearly 2 meters, the tags disappeared from the detection range of the antenna. Due to the directional range of the antenna, we had to hold it directed towards the surface of the water for best results. Therefore, we moved the antenna as the test subject swam to capture and read the tags. The reader was set to transmit radio frequency waves at the maximum power (32.5 dB). For the ease of carrying out the experiment and to record the maximum readings, our test subject swam parallel to the border of the pool and we moved the antenna as the swimmer moved in the pool.

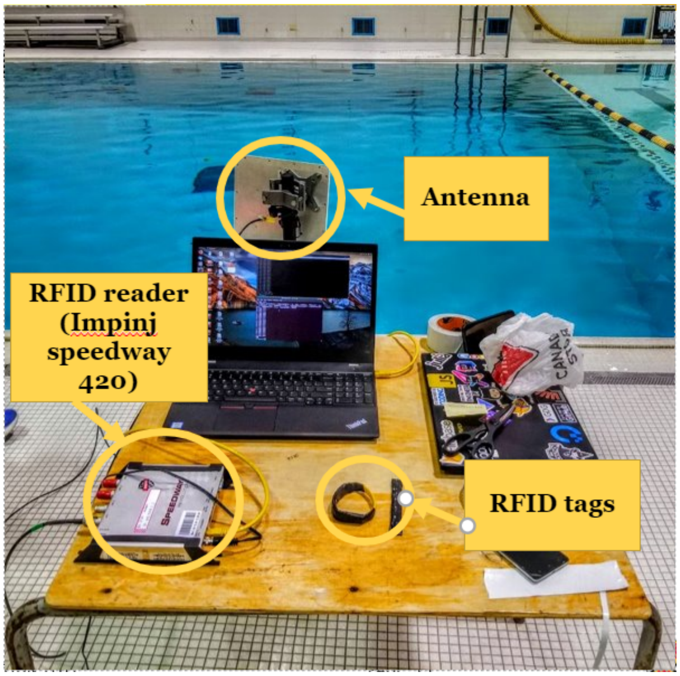

Figure 4: Experimental Setup

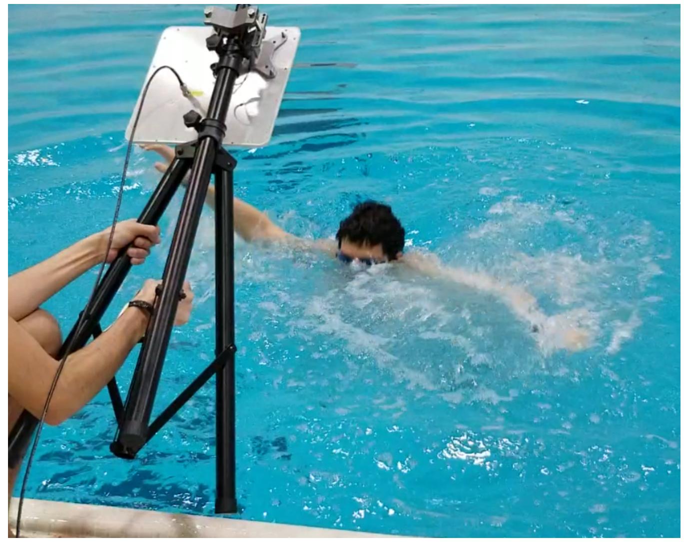

Figure 5: Drowning Motion

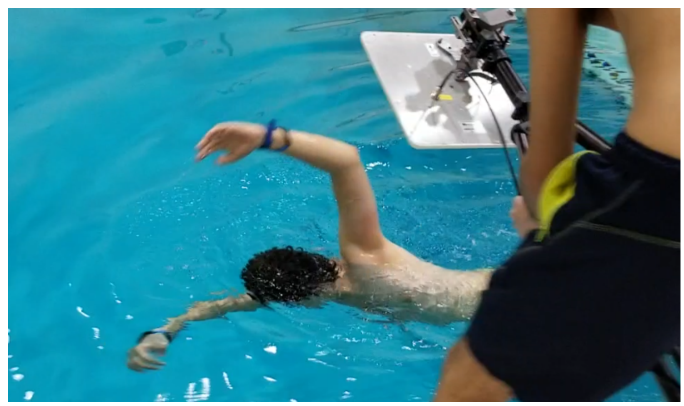

Figure 6: Swimming Motion

We collected the data in parts where the swimmer was requested to carry out different swimming strokes such as freestyle, breast-stroke, back-stroke, freestyle at one place, underwater, drowning, etc. Since it is not possible to directly collect data from a drowning person due to the safety hazard it produces, our test subject had to simulate drowning. We went through existing literature on drowning motion and were able to identify that drowning subjects display a typical range of motion when in distress. The subjects extend their arms in an effort to grab onto nearby objects and failing to do so causes them to bob vertically in the water. After demonstrating this motion briefly, they eventually inhale water that causes them to get permanently submerged in water. Our experimental goal was to record the initial motion of the subject when it begins to drown. Therefore, our test subject demonstrated drowning motion as close as possible to the researched pattern. Figure 5 and 6 illustrate the two different motions performed by our test subject.

The collected logs were further parsed using Python to create structured CSVs for analysis. We used an open source library called Sllurp for reading data from the RFID reader. Sllurp is a "Pure Python implementation of the Low Level Reader Protocol (LLRP)". The log files were saved in a '.log' format. Each log entry was in a JSON format containing a tag id, RSSI (Signal Strength) and 'tag last seen' timestamp in UNIX epoch format. We further wrote a python script to parse the data from the log files and store it in a csv file. To label the entries as drowning or swimming we used another open source library in python called Keyboard. Whenever the space key was pressed, the recorded data was labelled with a '1' indicating drowning and '0' otherwise for normal swimming motion. Therefore, we created multiple csv files in real-time for different swimming and drowning strokes, all labelled with either the swimming or drowning class.

5 RESULTS AND DISCUSSION

After the data had been collected, we figured out that there were gaps between consecutive readings based on the 'timelastseen' column. We filled those gaps appropriately by introducing equal interval readings to make the data continuous. An RSSI value of -100 dBm was allotted to the generated readings indicating that the tag was not seen during this period.

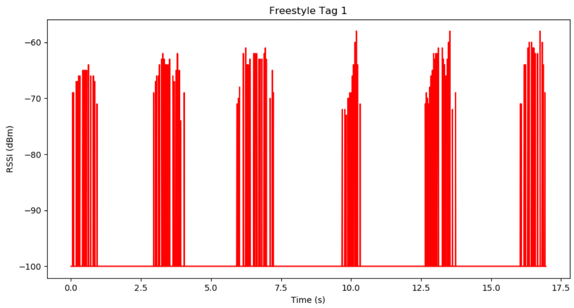

Figure 7: Freestyle Tag1

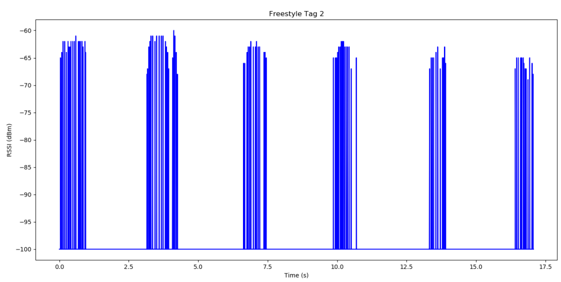

Figure 8: Freestyle Tag2

This processing step greatly increased the size of the data and due to different recorded lengths of subsequent strokes, the files had greatly varying sizes. To standardize all the files in terms of their length, we manually created chunks of 1000 rows for each swimming stroke. This was an essential step if we wanted to do time series classification, as the models expect that each sample must have the same number of rows.

To better understand the data, we plotted few graphs to see the trend of the signal strength values. As we can see from Figures 7, 8, 9, there are few spikes and then the graphs drops to -100. These spikes show some periodicity and we thus can decipher that swimming motion is periodic since the tag is read and unread in a periodic manner. On the other hand Figure 11, 12 depict non-periodic spikes. These spikes are random and of different signal strengths depicting that the swimmer was going through some distress or drowning event. Since the very nature of drowning motion is irregular, this non-periodicity is captured well in the plots.

Now that our data was prepared, we further researched on using Time Series Analysis for training our data to classify on swimming or drowning. As a first step we used an LSTM (long-short term memory) model based on RNN (recurrent

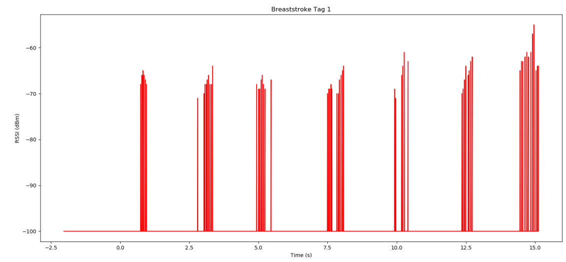

Figure 9: Breast-Stroke Tag1

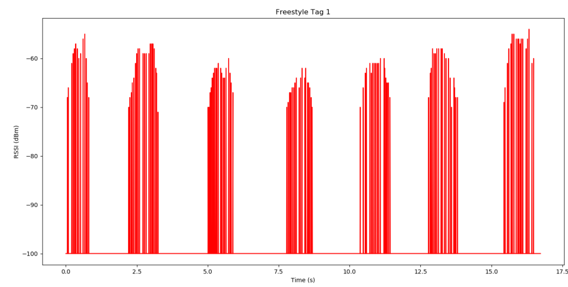

Figure 10: Freestyle In-Place

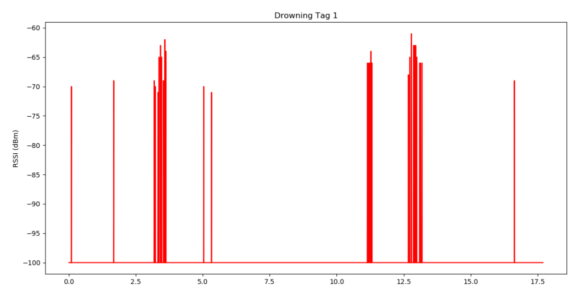

Figure 11: Drowning Tag1

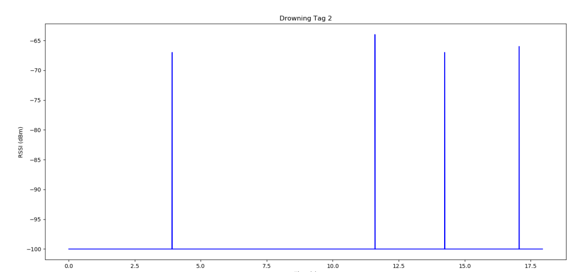

Figure 12: Drowning Tag2

neural networks) on our data to classify the samples. We divided our data into 35 training samples, 9 validation samples and 9 test samples. Each sample had 1000 rows of data. We tweaked around with the batch-rate, loss function, softmax layer, etc but our samples were getting misclassified. We interpreted that since our drowning samples were very less compared to the swimming samples, our model was failing to learn. Due to this disproportionately, our drowning samples were getting misclassified as swimming samples. We analyzed the current approach and proposed to break down the data into smaller chunks which would lead to much more data samples but with lesser number of rows. However, further investigation revealed that by creating smaller chunks we would actually loose the pattern that is presented in the time series samples. To retain the pattern in each sample, it was important that each sample must be at least a minimum length. Our current samples of 1000 rows each, represented 10 seconds of consecutive readings and this was the minimum we needed to retain the pattern in the data samples.
We further researched and decided to make another attempt by applying classical machine learning models after engineering the features. Previously we had 35 samples with 1000 rows each, where each row represented a single time step reading. We converted our data into 35 samples with 1000 features each, in order to transform the nature of the data from sequential to non-sequential. This allowed us to use models that are not inherently designed for time-series data, unlike the LSTM network we deployed earlier. We used KNN (K-Nearest Neighbors) algorithm with k-fold cross validation technique to tune the hyper-parameters. However, our samples were still being misclassified indicating that the model was failing to learn. We further used SVM (Support Vector Machine) algorithm with RBF (Radial Basis Function) kernel and utilized k-fold cross validation technique here as well. Our model still incorrectly classified the drowning samples. This was expected since the number of features for each sample was disproportionately large compared to the number of samples available. Therefore, no matter which model we deployed it was bound to fail to learn.

We hence conclude that Time Series Analysis is a good technique given the kind of data we have but to improve the accuracy of our model we require more data with proportionate amount of swimming and drowning samples. Furthermore, it will be beneficial to use multiple antennas for different signal-strengths since LSTM requires huge data-sets.

6 LIMITATIONS AND FUTURE WORK

In this section we elaborate on the limitations of our experimental setup and how it can be improved in the future for better results:

- We used a standard laboratory antenna for the experiment. As it turned out, the antenna had a limited power in broadcasting the query signal. This led us to perform the experiment very close to the periphery of the swimming pool where the subject moved parallel to the boundary. Therefore, the collected data did not fully cover the range of motion that a typical swimmer demonstrates.
- We used one antenna for performing the experiment. This meant that we had very limited coverage even when the swimmer was close to the boundary of the pool. To allow lateral motion the antenna had to be physically moved to keep it aligned with the subject and record data uninterrupted. More antennas attached to the same reader would have allowed us to cover a larger portion of the swimming pool.
- Using standard non-wearable RFID tags meant that they were prone to obstruction and signal attenuation when brought very close to the skin. This led to experimental problems where the tags had to be continually adjusted around the wrist to maintain communication. By using wearable RFID tags designed with extended antennas this problem could be mitigated.
- Owing to the limited experimental time and test subjects available, only a limited amount of data could be collected. Although, the data plots showed potential for identifying patterns for classification purposes, the restricted amount of data meant that we were unable to train a classifier using Machine Learning models.

In the future the above stated limitations will have to be dealt with. We are confident that if the experiment is performed again over a longer period with more test subjects and while also ensuring that the hardware setup is better suited for the task, we will be able to collect sufficient data to train a Machine Learning model.

7 CONCLUSION

This report presents a technology capable of identifying a drowning person in a swimming pool by relying on wireless signals back-scattered from passive RFIDs. This marks an important step in the budding field of human activity detection using RFIDs. It is also one of the first technologies that leverages the limitation of RF signal propagation through water to an advantage in monitoring human activity in a swimming pool. The setup uses standard laboratory equipment i.e. off the shelf RFID tags and an Impinj RFID reader. The experimental analysis presents the potential of using the technology in production while ensuring low deployment costs. The results also illustrate the potential of using the technology for further applications such as counting human subjects in a water-body and personal fitness tracking in a swimming pool.

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