Detecting and Visualizing Rip Current Using Optical FLow

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Abstract

Rip current are fast moving narrow currents that are strongest near the beach. These type of currents are dangerous for not only novice but also experienced swimmers. Once caught in the current, the flow of the water pulls the person away from the beach. Many people in panic try to swim against the current, end up drowning due to exhaustion since these currents are usually faster than the speed at which one can swim. They have led to more than 100 beachgoers death due to drowning per year in United States only.[5] For a knowledgeable person, these rip-currents are easy to spot, but a threat to many people who are unaware of rip-currents or how to identify them. In this paper, we discuss a novel approach that uses Optical flow to detect rip currents, and how to visualize them.

Keywords: Time-dependent, vector fields and visualization

1 Introduction

The rip currents are very fast moving narrow channels, which if caught in one can cause a person to drown. The currents pull a person away from the shore. Instinctively, people try to swim against the current, but it results in exhaustion and eventually drowning.

According to United States Lifesaving Association, there are four ways to identify rip currents. They are as follows:

- A channel of churning, choppy water;
- A line of sea foam, seaweed, or debris moving steadily seaward;
- Different colored water beyond the surf zone; and
- A break in the incoming wave pattern as waves roll into shore[5].

The rip currents are caused along the coastline where break waters occurs. Certain circulation cells are formed when the waves break strongly at some regions and weakly in others. These generally occur at beaches with sand bars and channel system nearby. This water flows back towards the sea following a .narrow path, forming a rip current[5]

In this paper, we discuss how we can leverage the optical flow algorithm to identify and represent these dangerous rip current.

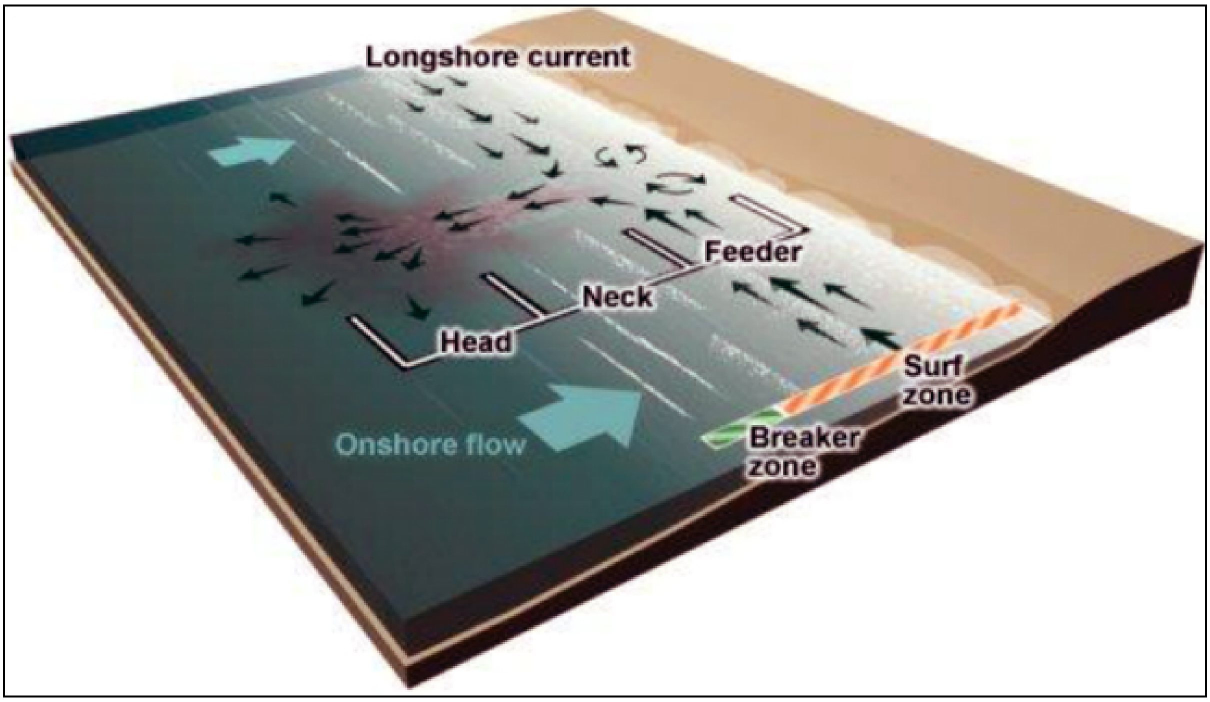

Figure 1: Formation of a rip current (Image courtesy of National Oceanic and Atmospheric Administration, National Weather Service)[4]

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2 Motivation

According to a study by United States LifeSaving Association, the annual number of deaths caused by rip current exceeds 100. There are about 80% of the rescues due to people almost drowning in rip currents. Rip currents usually flow at the speed of 0.5 m/s or 1.1 mph. Some of them can also speed up to 2.5 m/s or 5.6 mph. This is faster than most people can swim[5]. Hence, when in panic, people start to swim against the current, and eventually loose consciousness due to exhaustion. This, if went unnoticed, can lead to drowning.

From expert swimmers to first-timers, rip currents have killed more Americans than hurricanes, in an average year. Most lifeguards and experienced people are able to detect the position of the rip currents, they look for various signs as mentioned above[5].

A study was done where around 97 surveys at Pensacola Beach, Florida were conducted. It was observed that majority of the participants were confident that they could identify a rip current, whereas less than 20% were successful in identifying these currents accurately[6].

An application that can detect rip currents in oceans, can help inexperienced people identify these currents. This will help in avoiding deaths of swimmers as well reduce the number of rescues performed by the lifeguards who also put their lives in danger in order to save people in need.

3 Related Work

Over the years, there are many research done by universities to understand the behavior of these currents. Many beaches have also set up signs that explain how to safely come out of a rip current if one is caught in it. The University of Delaware Sea Grant College Program and United States Lifesaving Association, have setup a website that explains the formation and safety precautions of the rip currents[3][5]. Various other departments in University of Delaware and other universities such as Stevens Institute of Technology, New Jersey, Johns Hopkins University, Maryland and many more are pursuing research to break new grounds in understanding behavior of these rip currents. They are also helping National Weather Service and local beach controls to improve the prediction of these rip currents[2].

Apart from these, a patented device was created by Gregory Perrier in 2001, an Automated Rip Tide Detection System, that took various images of the said rip tide, and mimic the human perception to identify these rip tides with the help of neural networks. A camera is used to take pictures, and image processing is done to enhance signs that differentiate the rip tides from the normal waves, such as texture, color and direction. Rip tides are essentially powerful currents caused by tide pulling the water through an inlet along a barrier beach, whereas rip currents are caused due to all the water escaping the shore tries to take a single path[7]. They assume that the rip currents leave the shore perpendicularly, whereas the normal waves hit the shore obliquely. This is followed by training a neural network model, which trains based on the information available from the processed camera images to differentiate rip vs normal currents. [8]

Another patented device was created by Earl Senchuk and Michael Rucinski which needs to be anchored in the water body. This device then monitors the current speed of the water. The device then compares the current speed with a certain amount of threshold. As soon as the speed crosses this threshold, it sends a rip current warning. To be effective, the device must be placed at or near potential rips. It also requires power and maintenance to operate properly [9].

Both of the patented devices discussed in the paper require specialized modules for processing the data and generate a warning, which makes it inaccessible to a general population. The first approach would require the device to be trained on different beaches, to identify the rip tides at different locations. This is necessary since the underwater floor structure may not be the same for all beaches. While rip tides do recur in one place, they are highly unpredictable and a change in the location would require the device to be re-trained or relocated to monitor them. Also there are some rip currents that are not necessarily perpendicular to the beach. These would be hard to detect with the said device due to the assumptions made in the beginning.

This has led us to device an application, that can run on a simple computer, but ideally on mobile phones which are portable and affordable. Our approach is based on the optical flow from a short video sequence of the waves. Identifying the regions with strong opposing flow as the incoming waves and mark them as rip currents. Visualizing capability of such as this can help save lives.

4 Methodology

4.1 Optical-Flow

The Optical flow algorithm is used to capture the apparent motion of the object. There are many different algorithms to perform Optical flow and they all basically consider the same two assumptions[1]:

1. Pixel intensity of an object between consecutive frames remain the same
2. Neighboring pixels follow the same motion.

One such Optical flow algorithms called is Lucas-Kanade. We selected this algorithm since it is highly sensitive in capturing small motions in between frames. This property is very good at dynamic texture as water. The algorithm is explained below:

Consider a pixel with intensity $I(x, y, t)$ in the first frame, which moves a distance of dx, dy in time dt in the second frame. A time dimension is added to represent how much the pixel moves in a given time. Taking the first assumption into account we can write the following equation:

$$I(x, y, t) = I(x + dx, y + dy, t + dt) \tag{1}$$

Assuming that dx, dy is small, the image constraint at $I(x, y, t)$ with Taylor series leads to following equation:

$$\frac{\delta I}{\delta x}\frac{\delta x}{\delta t} + \frac{\delta I}{\delta y}\frac{\delta y}{\delta t} + \frac{\delta I}{\delta t} = 0 \tag{2}$$

$$\frac{\delta I}{\delta x}u + \frac{\delta I}{\delta y}v + \frac{\delta I}{\delta t} = 0 \tag{3}$$

$$I_x u + I_y v + I_t = 0 \tag{4}$$

Based on the second assumption that the neighboring pixels have a similar motion, the Lucas-Kanade algorithm uses a 3x3 neighbourhood around that point and obtains the values of (I_x, I_y, I_t). There are 9 points in consideration, hence we get 9 equations and we have our two unknowns (u, v) which is our velocity vector. This results in over-determining of the unknown variables. A least square fit method is used to find the velocity vector. We use the following equation to determine the velocity vector:

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} \Sigma_i {I_{x_i}}^2 & \Sigma_i I_{x_i} I_{y_i} \\ \Sigma_i I_{x_i} I_{y_i} & \Sigma_i {I_{y_i}}^2 \end{bmatrix}^{-1} \begin{bmatrix} -\Sigma_i I_{x_i} I_{t_i} \\ -\Sigma_i I_{y_i} I_{t_i} \end{bmatrix} \tag{5}$$

4.2 Representing Direction and Magnitude

Now that we have obtained the velocity vectors between two frames, we are looking for a good representation that will indicate the individual directions easily. One way is to represent discrete points on the frame with arrows, gylphs to indicate the direction and the magnitude of the vector field. The only problem with this representation is that, the motion between two frames is very small which makes it difficult to get a sense of the water movements. Hence, we decide on color mapping the direction using a color-wheel instead. This color-wheel is inspired by John Savard[10]. Here we have divided all directions, i.e, degrees from 0 to 360 into 36 bins. Each color representing a range of 10 degrees as shown in Figure 2. For example, red means from the center towards lower right with the range from $0°$ to $10°$.

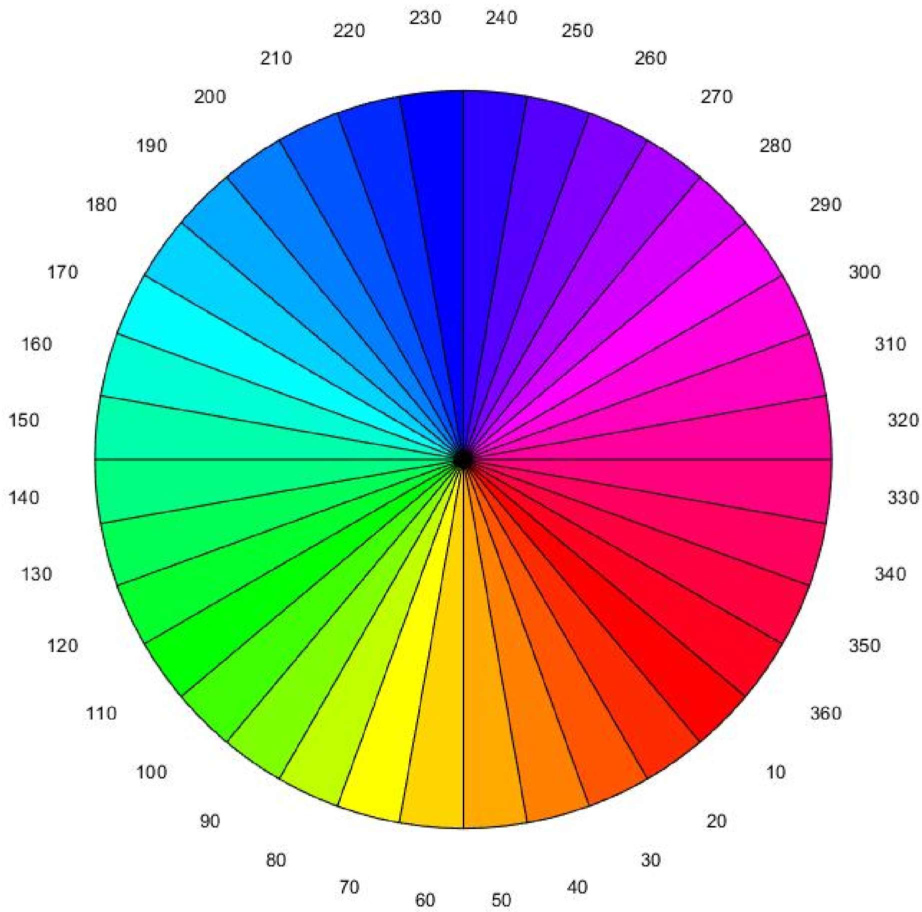

Figure 2: Color-wheel: Representing the mapping of direction to color

While the direction is mapped to hue, we map magnitude to grayscale with values in the range $[0, 1]$ 0 represents no movement at all and 1 represents the fastest displacement of a pixel(or in this case within a neighborhood of 20x20 pixels) between two frames. Figure 3 represents the direction between two consecutive frames, along with a histogram recording the frequency of each direction.

The Figure 4 represents the magnitude of the velocity, along with a histogram of magnitude values. White is for highest speed value or 1, while black is for no movement or zero.

4.3 Isolating the Rip Current

Now that we have the direction representation of the frames, we want to threshold the figures to obtain only the direction and magnitude of the rip current. We do this by first finding which

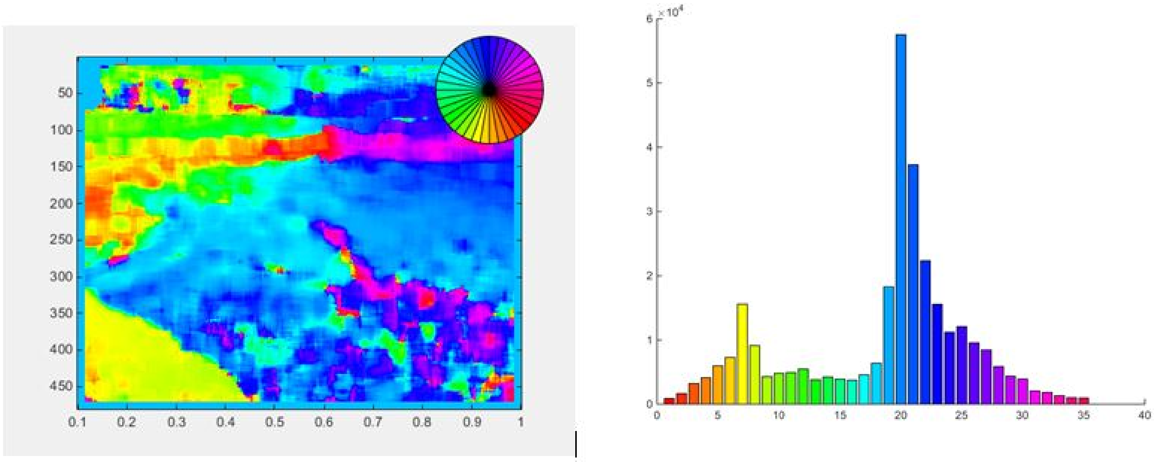

Figure 3: Direction values mapped to color and hue(left) Histogram of each direction(right).

color represents the motion of water going back into the ocean. Let us first take a look at the first frame of the video show in Figure 5.

By observing the frames and the corresponding histogram, we can see a two predominant and opposing value directions: incoming waves and outgoing waves. We decide to threshold using a range from 160° to 230° as seen in Figure 2 to extract the region with outgoing directions. Any value that falls outside this window is set to zero, otherwise we keep the values as it is. This helps us to remove directions that are not going towards the ocean, thus identifying our potential rip-current. The result of this thresholding is seen in Figure 6.

Next, We observe the magnitude image, which now only represents magnitude of the water flowing back towards into the sea. Though the thresholding of the direction has removed most of the unwanted motion, there is still some motion seen where the sky and the rocks are located. This motion can be cause by many reasons. One of the main reasons why we see slight motion in the sky or the rocks is because of the hand movement of the camera while taking the video. To remove this, we now implement thresholding of the magnitude image, to only retain the higher values of speed. The result of thresholding is shown in Figure 7. Note: There is a huge peak at the first bin, since we have set all magnitude values of speed that had direction falling outside of the range 160° to 230° to zero.

4.4 Representing the Rip Current

In this subsection, we decide how to represent the rip currents. So far, by means of thresholding, we have obtained values of velocity that has the desired direction, that is going back towards the sea and with high velocity magnitudes. As evident from Figure 7, the area of high magnitudes are not continuous. Also, these regions obtained from consecutive frames contain noise artifacts as well as regions that may in fact not be significant. Given the typical wave periods to produce strong waves that create hazardous rip currents, we use a sliding time window of 3 seconds or 90 frames from 30fps video clips to smooth out noise and identify strong and more persistent rips We do this by creating an accumulation buffer with the same resolution as each image. Each element in the buffer is incremented by 1 if that pixel was identified as being a rip in an

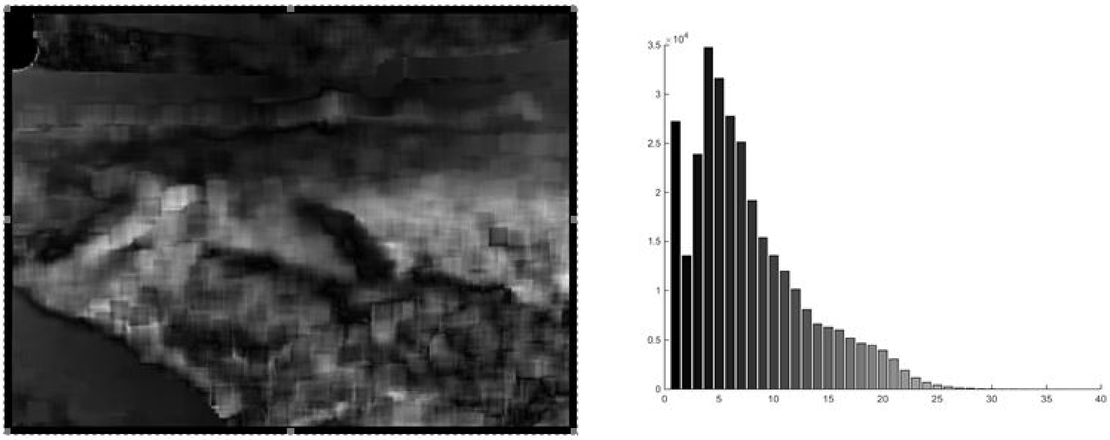

Figure 4: Magnitude value as a gray image(left) and Histogram of the Magnitude values(right).

image pair sequence. This is done for 90 frames and the values in the accumulation buffer are normalized.

The image in Figure 8, shows the result of the accumulator buffer. This accumulator buffer is after 3 seconds into the video.

The next step is to find bounding boxes for the patches in the accumulator. We need these bounding boxes to be aligned to the direction of the rip current. To obtain the direction of the rip current, we take the highest bin from the selected window that we used. The Axis Aligned Bounding Boxes(AABB) are shown in Figure 9. This AABB is obtained by following the steps below:

- Perform a binary threshold on the Figure 8.
- Rotate the image by the main direction of the rip current.
- Find the minimum bounding box for the patches in image.
- Once the bounding box is found, rotate the image back to get AABB on the un-rotated image.

Note that, small patches are ignored since their bounding boxes are very small, which will make their representation difficult to perceive.

Once the AABB is obtained, we draw an arrow within the box aligned with the flow direction such that it's length is set to length of the AABB parallel to the flow direction. We then highlight the area representing the rip tide and add an arrow to represent the rip. Note that, to get a continuous area of rip tide, we perform hole filling and clearing up very small patches. The result of the procedure is shown in Figure 11.

The arrows now represent the direction of the rip, and the red patches shows where the waves are fastest in a frame. The width of the arrows also represent the average magnitude of the velocity in the respective AABB. To get the average magnitude, first we find out the average magnitude of all pixel locations for 90 frames. Then we perform an average of all the values

Figure 5: First Frame of the Video

falling in the AABB that we found. This magnitude is used to increase or decrease the width of the arrow. Thus every patch represents an average magnitude over time (90 frames) and space (within the AABB). We calculate these results using a sliding window of 90 frames for the entire video. We combine the resulting frames, to obtain a full video that indicates the dominant direction and average magnitude of the rip current over the course of the video.

5 Conclusions and Future Work

The Lucas-Kanade Algorithm, is very robust for finding the direction and magnitude of the motion of water. This technique can segment the rip current successfully by thresholding direction and magnitude separately based on the pattern of the histograms. It is also robust against noise due to small camera movements, since we take an average over 90 frames.

So far we have shown that this approach works. However there are lots of room for improvement. The technique currently only looks for and indicates only one continuous range direction. We want to make the algorithm smart enough to recognize more than one rip current at a time, which differ in directions. We expect that such an extension will allow us to identify rip currents that extends out further to sea and possibly a curved path along the way.

We would also like to make improvements in run time of the Lucas-Kanade Algorithm, which was implemented in MATLAB $R2014b^{TM}$. This is currently the most time consuming step in the technique. Once improvements are done to this step, we can shift the code to a mobile platform, and make it publicly available to everyone.

Code can be found at the following link:
`https://github.com/AryaPhilip/RipCurrentDetectionAndVisualization.git`

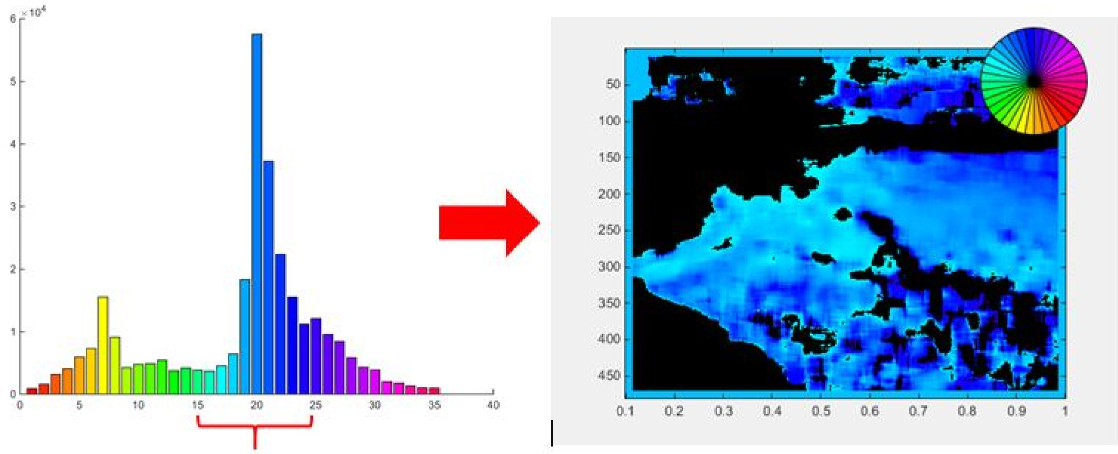

Figure 6: The direction figure after applying threshold and masking out the regions that fall below the threshold.

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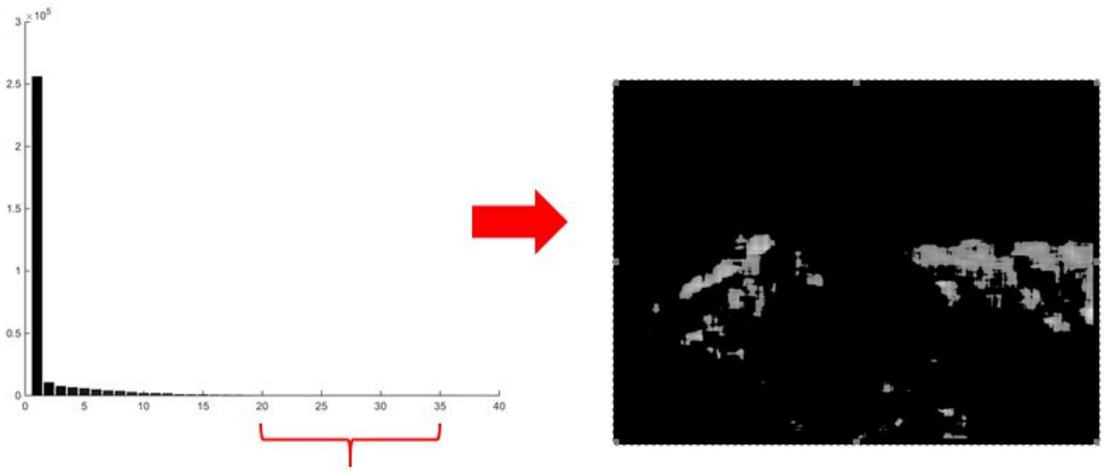

Figure 7: The Magnitude image (right) showing only regions with values indicated in the histogram (left).

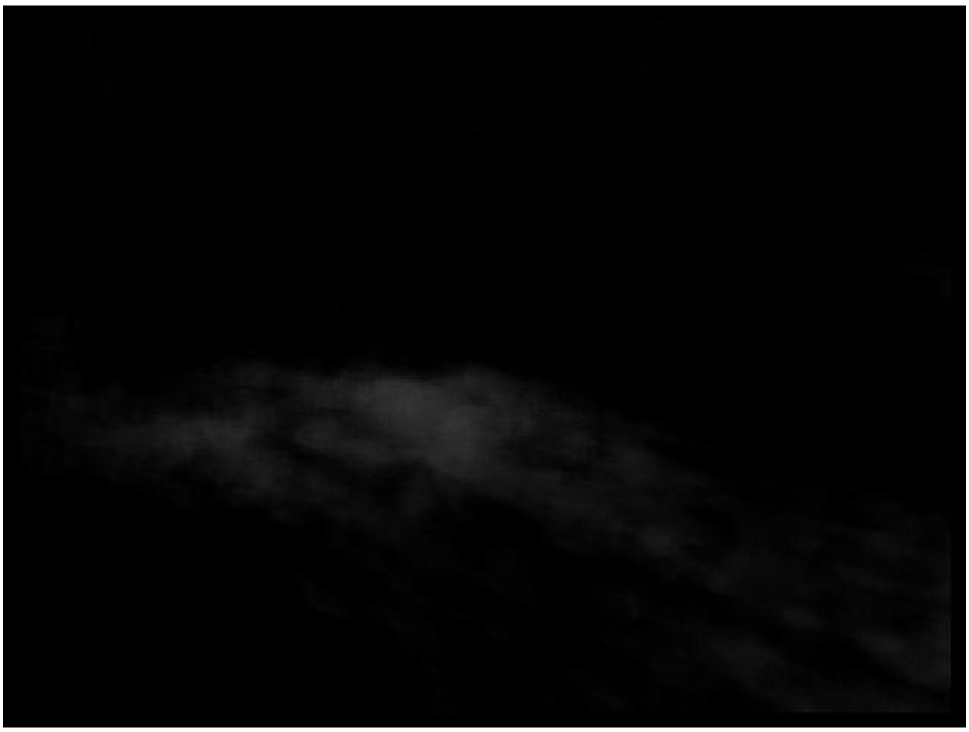

Figure 8: Contents of accumulator buffer for 90 frames. Cell counts have been normalized where black is zero and white is 1.

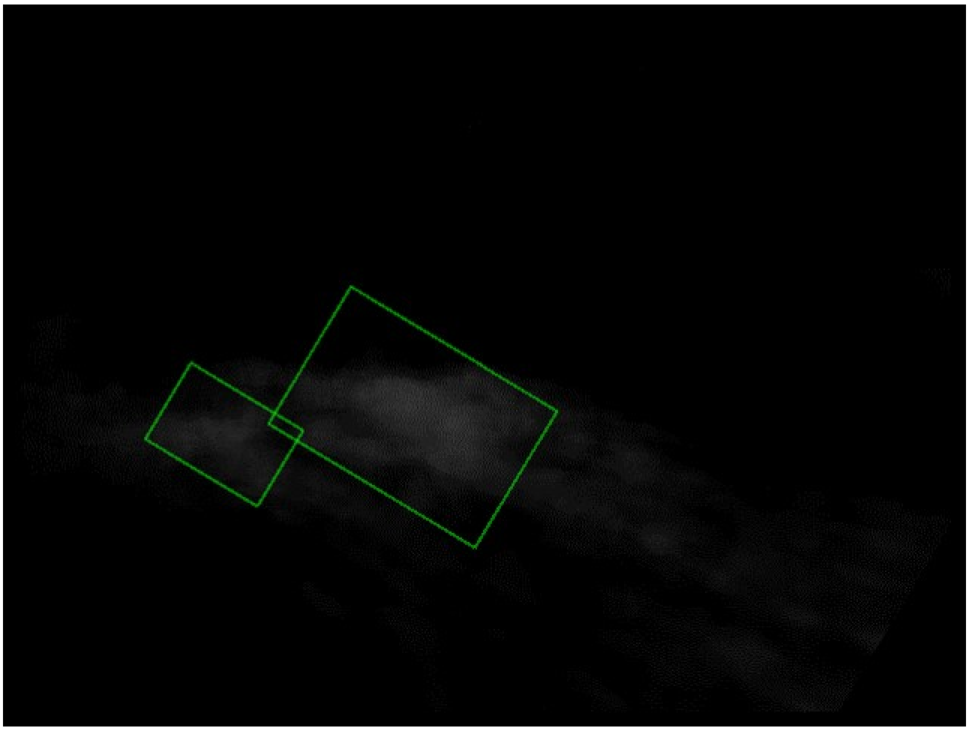

Figure 9: Axis Aligned Bounding Box

Figure 10: Representation of Rip Current

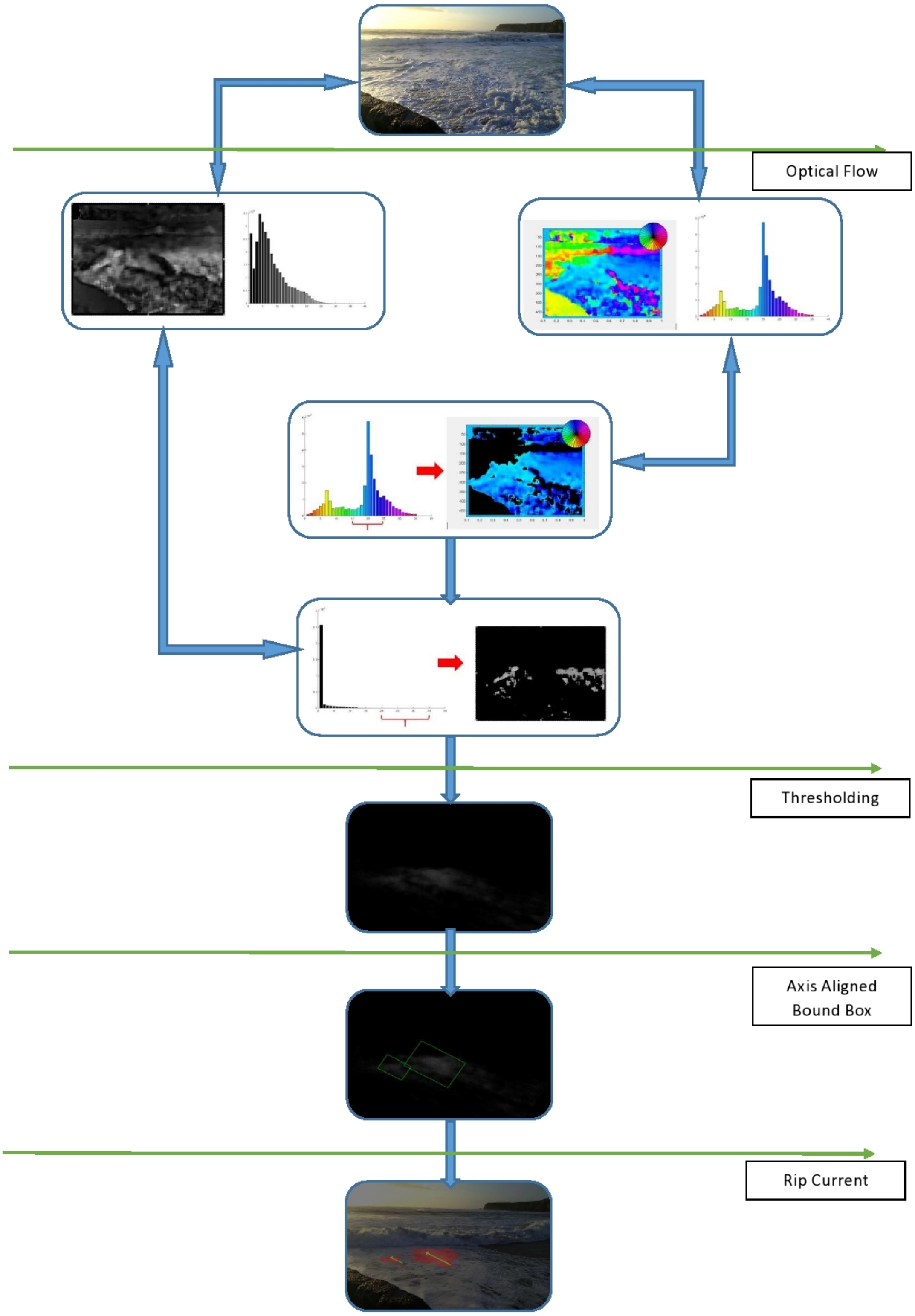

Figure 11: Flowchart for Detecting and Representing Rip Currents.