Quadcopter-based Stagnant Water Identification

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***Abstract*—In recent times, there has been a sharp increase in dengue and malaria, especially in urban areas. One of the major reasons for this health hazard is the number of locations where one can find stagnant water. These locations are large breeding ground for fast multiplying mosquitoes, and other insects. Areas include traditionally uncovered gutters, and also terraces of high rise buildings, and shades above windows (popularly known as chhajja)– areas that are hard to reach and access.**

In this paper we propose the use of a quadcopter to inspect such areas and identify stagnant water patches. Water being specular in nature tends to confound traditional image processing methods. Further the use of a non-traditional camera mounted on a quadcopter presents new challenges. We provide methods to get past such hurdles.

I. Introduction

Dengue [1] is a troublesome debilating disease with no known preventing vaccine, or cure. Doctors advocate that the best way to avoid this disease is to avoid being bitten by mosquitoes which is virtually an impossibility for many people in India. The greatest risk of contracting dengue (pronounced DENgee) is in the Indian subcontinent.

Technology is a must in tackling this situation. The risk of disease can be reduced by using insect repellents. In our institute, the common method has been the spraying of insecticides. Reports in the media [2] indicate that China has flooded a small island releasing half a million sterile mosquitoes to dominate the potent mosquitoes. Such measures have unknown and unforeseen environmental impact on the eco-system. Regardless, researchers are convinced that there is no one single magic bullet to tackle the disease.

Our work, started prior to the announcement of "Project Premonition," is similar to that of [3]. Instead of attempting to destroy the mosquito, we seek to detect the reason for the increased outbreak, especially in urban areas. The work reported in this paper complements that of [3] — the goal in [3] is to "catch wild mosquitoes" (typically in the outfield) by creating novel mosquito traps, and then to test mosquitoes for pathogens. New traps are placed by drones, and retrieved by drones. In contrast, this paper emphasizes the need for identifying the location of these traps.

One of the major reasons behind the growth of mosquitoes is the continuous existence of *water puddles* around residencies in urban India. The virus is carried by mosquitoes, and these breed in stagnant water. *Can we detect stagnant water?* When we surveyed terraces (Fig. I) and "chajjas" of various buildings in our institute, we found split AC air conditioners dumping condensed water. Such areas can be surveyed using autonomous quadcopters.

This is a pre-print version of a paper accepted to NCVPRIPG 2015, IIT Patna.

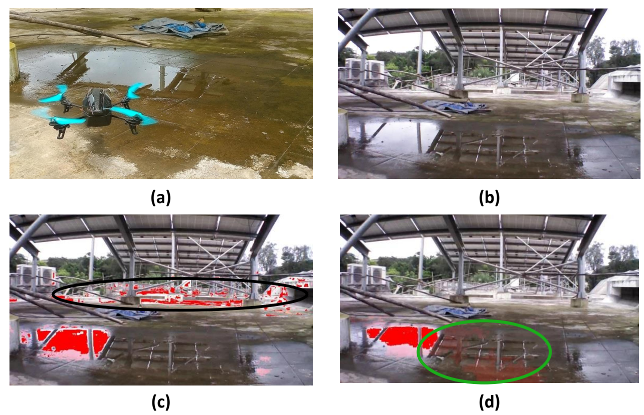

Fig. 1. (a) Our hovering quadcopter (b) A typical rooftop on campus (c) Earlier method [4] applied, and output marked in red (d) Our output. Notice (marked as black oval in (c)) that [4] confuses non-puddle patches as puddle. Also, note (marked as green ellipse in (d)) that [4] is not able to detect puddle which are dark.

Contributions: The scientific challenge in identifying water is that it is specular in nature, and acts like a mirror. Water is like a chameleon changing its color depending on the environment, and there is no easy way of saying "this is water" based on its appearance. In this paper, we propose the use of an old paradigm of optical flow for the novel application to stagnant water detection. We couple it with a modern SVM-based method of classification. Results shown in this paper are convincing.

Related Work The method in [5] for detection of water relies on the chaotic nature of water's dynamic texture to exploit a measure of entropy over the trajectories obtained from optical flow trackers over several frames. [6] has introduced a descriptor which is tolerant to the flip transformation and even non-rigid distortions, such as ripple effects. *These methods and others in the literature focus on the turbulent aspects of water*, largely absent in our application that focuses on stagnant water. Our method is closest to that of Rankin et al. [4], [7] who have implemented a rule-based water detector based on sky reflections. These rules are established based on an analysis of images captured in wide-open areas on cross-country terrain. Not only do we have new methods, *our datasets are captured in urban areas using a quadcopter and thus these rules seem unlikely to be readily applicable.*

II. Methodology

Our method is based on a combination of color based method with an optical flow based method. We establish the need for the combination in the first two subsections.

A. Appearance-based Detection

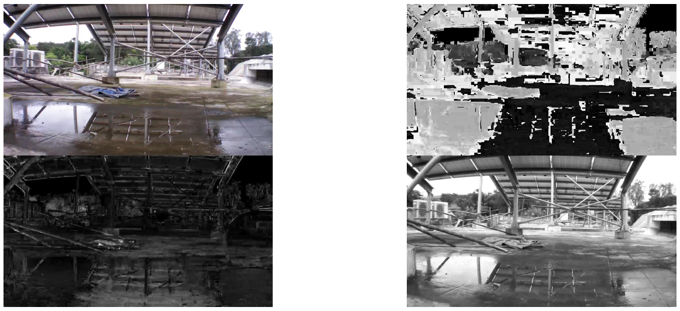

Fig. 2. An image (top left) and the HSV components. The puddle has low saturation (bottom left) but high intensity (bottom right). The hue is indeterminable and is based on the environment.

Under ambient lighting conditions, puddle areas display high brightness and low saturation as can be seen in Fig. 2. Features based on these are fed to an SVM classifier. Training an SVM is a labour intensive task. To reduce the effort, we have developed a tool shown in Fig. 3.

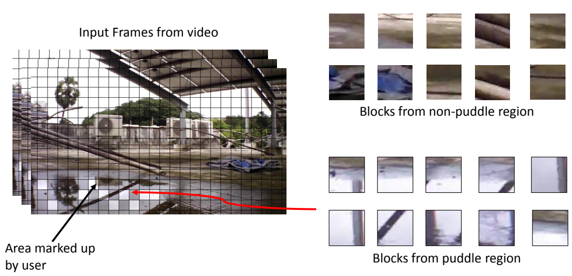

Fig. 3. The process for creation of training data. The user selects the stagnant water area by drawing a contour to produce 'positive' and 'negative' data.

Failure of SVM-based methods: The SVM detector is good at detecting regions of sky reflected off a puddle. In the HSV color space, these regions have low saturation (S) and high brightness (V) values, and are picked up with high reliability by the HSV histogram feature based SVM detector. However, false negatives are also produced since other reflected regions such as trees, buildings, etc. are usually classified as non-puddle regions as many of these characteristics is shared by negative images in the training data set.

B. Optical flow based Detection

Fortunately our images are captured by a moving quadcopter. The optical flow measures apparent motion of objects in a scene caused by relative motion between camera and object. The magnitude of the optical flow is high for objects that are close in comparison to objects at a distance. Fig. 4 shows the magnitude of optical flow calculated from two images.

A recent thesis [8] has one of the state of the art algorithm for optical flow. One requirement is the need for spatio-temporal smoothness constraint which can be challenging because of the jerky movement of the UAV. To resolve this, we use the Inertial Measurement Unit (IMU) data available on the quadcopter to synchronize positional information with the video sequence captured by quadcopter. In short, we select the frame pair which are spatially the closest, among a set of competing temporally adjacent frames.

Fig. 4. Optical Flow. Left, Middle: Frames taken from positions which are d units apart in 3D world. $0.01 \leq d \leq 0.1$. Right: Magnitude of optical flow. We observe that the magnitude of optical flow in the reflective parts of the puddle is relatively low.

Failure of optical flow: Optical flow is essentially being used in a depth from parallax mode to exploit the fact that still puddles behave like mirrors. The scenery reflected by such puddles is usually at a much greater depth than the immediate surroundings of the puddle. Optical flow is largely independent of hue and saturation. For the same reason, however, optical flow as a means of detecting puddles will fail to report true positives when the object that is being reflected is close by. In such cases, the saturation and intensity values are useful.

Yet another reason for the failure for the optical flow is the inability to distinguish true "far away" regions versus imagined far away regions due to the mirror-like properties of water. To handle these false positives, we devise a horizon mask based on the principle that water flows down.

C. Combined approach

Horizon Mask: The change in depth for far-away scenes as well as their reflections on puddle, in consecutive frames, are hard to distinguish. In previous work [7] such issues are avoided by discarding a fixed-portion of image corresponding to far-off regions, enforced by constrained input capture method. Due to inapplicability of such constraints in the comparatively agile input capture conditions of quadcopter, features derived from urban environment are utilized for finding plausible puddle regions. In urban setting, the high availability of structures in surroundings, having distinctly flat surfaces and rectilinear silhouettes, enables use of edge-detection based methods to bound planar regions that can contain puddle. Applying the Hough transform with calibrated parameters followed by length-based selection of lines detected, a upper boundary for puddle region called 'Horizon' is found. The Horizon is in turn used to create a binary mask to be applied to local scores from other techniques before normalization.

These observations suggested a novel combined approach as sketched in Fig. 5.

III. Experiments and Results

All our experiments have been completed with the inexpensive consumer quadcopter called Parrot's AR Drone. We remark that one should not compare expensive military grade drones with such inexpensive drones. For the purpose of showing the efficacy of this paper, we also took a picture of the scene from a distance with a 5 mega-pixel camera

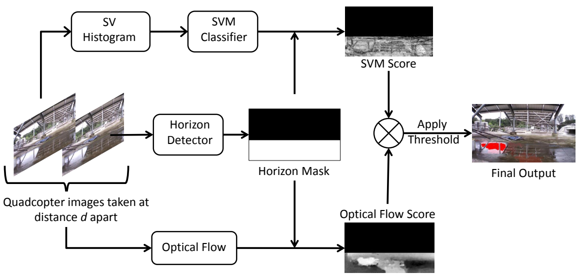

Fig. 5. Overall architecture.

for the reader to better understand the scene. We covered urban places such as terraces, constructions sites, building backyards, pumping stations, and so on. We have captured around eight different types of datasets, each having around two-three minutes of video (around 3000 frames each). Due to page restriction, and file size restriction, in this paper, as well as in the supplementary material, we have shown only representative frames from captured videos. Frames not having any stagnant water are not shown. The source code is available at [9] while the data sets we created for this work can be downloaded from [10].

Comparison: We compare our method to [4] on representative images since the methods in [7] do not apply. It can be seen from Fig. 6 that in all images, [4] is confusing bright patches as puddle patches (note red patches on walls, sky etc. in middle column in Fig. 6). Also, [4] is not able to detect textured puddle images (as seen in the first row in Fig. 6). (The confidence in detection is indicated by red hue in the output image. So, darker the red tinge, higher the confidence in detected water region.)

IV. Conclusions

Earlier in the introduction, we emphasized the need for detection of stagnant water in hard to access areas. In the remaining parts of the paper we proposed a novel technique using a quadcopter. The method proposed involved assigning a probabilistic measure to image patches in input image frames, indicating likelihood of it being a puddle. The measure was obtained by combining scores from an SVM-based classifier, and an optical flow classifier. It is shown that our approach produces better results in a variety of urban scenarios.

The main scientific contributions have been in addressing the specular nature of water since water takes the color of its neighbourhood in a puddle. Further an unmanned aerial vehicle can be quite jerky. We combined the IMU data on the quadcopter with the acquired imagery so that the state of the art optical flow method can be used.

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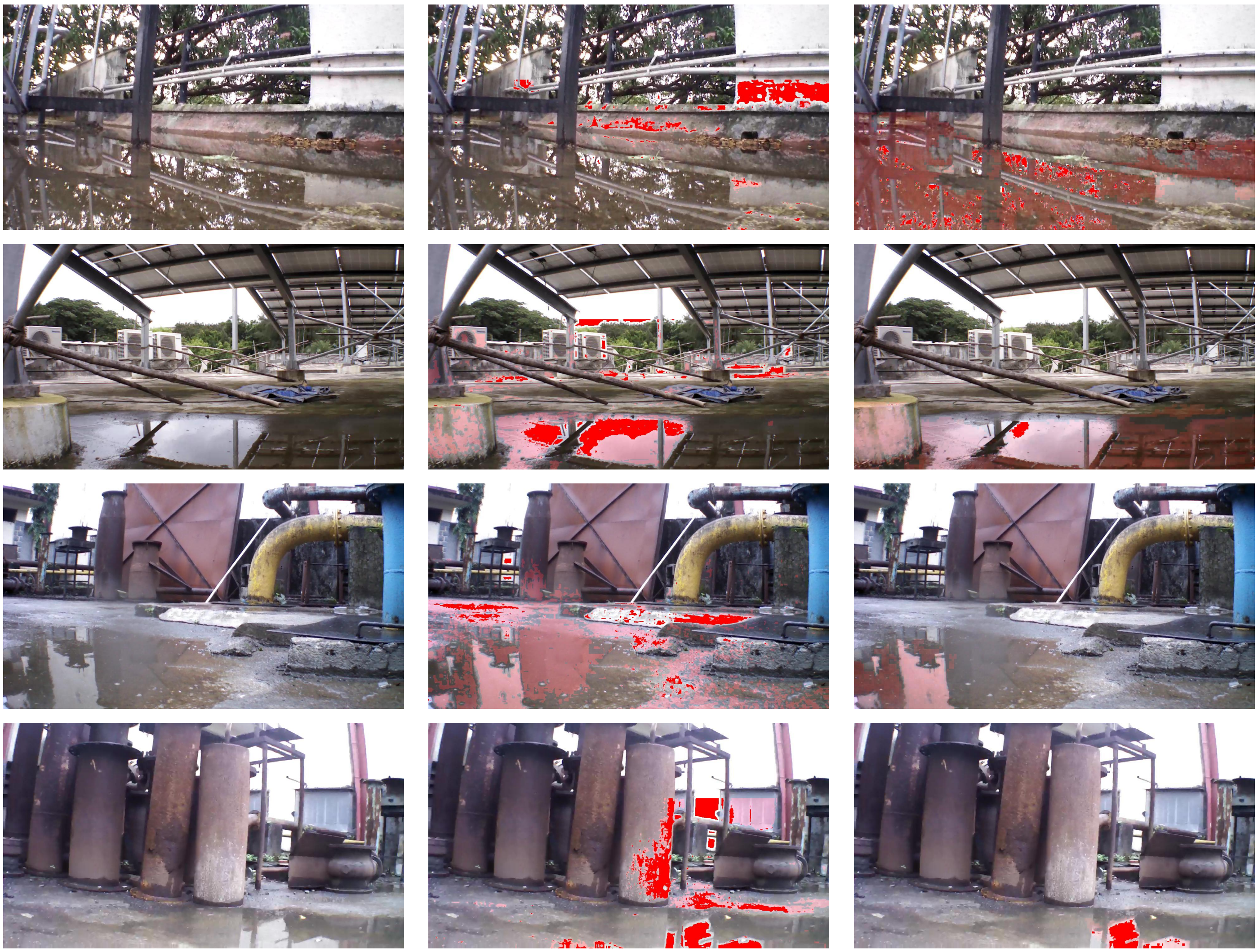

Fig. 6. Comparison of proposed method with [4]. Confidence in detection is indicated by red hue in the output image. So, darker the red tinge, higher the confidence in detected water regions. **Left:** Original Image, **Middle:** Output of [4] **Right:** Proposed method. It can be seen that [4] is unable to detect textured puddle regions. Also, several false positives are seen to appear in the middle row. Our method is sedate and sufficient to alert health workers.