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# A Novel Approach for A Double-Check of Passable Vegetation Detection in Autonomous Ground Vehicles

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*Abstract*— **The paper introduces an active way to detect vegetation which is at front of the vehicle in order to give a better decision-making in navigation. Blowing devices are to be used for creating strong wind to effect vegetation. Motion compensation and motion detection techniques are applied to detect foreground objects which are presumably judged as vegetation. The approach enables a double-check process for vegetation detection which was done by a multi-spectral approach, but more emphasizing on the purpose of passable vegetation detection. In all real world experiments we carried out, our approach yields a detection accuracy of over 98%. We furthermore illustrate how the active way can improve the autonomous navigation capabilities of autonomous ground vehicles.**

## I. INTRODUCTION

Regarding to the literature of robotics research, to increase autonomous ground vehicle (AGV) safety and efficiency on outdoor terrains the vehicle's control system should have different strategies and settings for individual terrain surfaces. To enable more autonomous tasks in complex outdoor environments, the vehicle must have more "feeling" and "seeing" [9][10][11][12][13][14]. While good terrain models and terrain classification techniques are already available to deal with a variety of terrain surfaces, the key limitation of outdoor autonomous navigation is to cope up with domains at which the vehicle has to navigate through tall grass, small bushes, or forested areas. Since, current perception systems can not do effective obstacle detection in these conditions, an idea to detect vegetation areas and try to set up a new definition of an obstacle as vegetation is really appreciated. Indeed, a lethal obstacle is conventionally defined as a solid object with significant height, which soon presents problems. In situations such as a cornfield, a field of thick and tall grass, there may be dense geometric obstacles on all sides of the robot. This can lead to the vehicle getting stuck. In contrast, the vehicle can try to drive over vegetation without any damage that enables more autonomous tasks in agricultural applications, rescue mission, or even military mission.

Recently, there was large amount of research investigating on vegetation detection based on vision techniques and LIDAR-based terrain models [3][4][5][6][15][16] [7]. However, different species of vegetation have different colors, textures, structures as well as shapes. Also, illumination changes in outdoor environments cause a huge impact on the quality and reliability of the detection methods. These restrict the applicabilities of those approaches for the purpose of detecting vegetation in general.

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Alternatively, vegetation needs sunlight to survive, using chlorophyll to convert radiant energy from the sun into organic energy. Chlorophyll exhibits unique absorption characteristics, absorbing wavelengths around the visible red band (645 m), while being transparent to wavelengths in the near-infrared (NIR) (700 m)[17]. These characteristics of chlorophyll are commonly used to design indices to estimate the local vegetation density in the satellite remote sensing field [18][19][21][20]. [1][2] and [8] investigated this discriminative property of vegetation to apply for detecting vegetation in autonomous ground vehicles. However, those works remarked that on-board navigation reveals much more complication than in multi-spectral satellite or airborne, with presence of shadow, shining, under- and over-exposure effects. Whereby, light spectral reflectance of objects changes significantly against these effects, thus, a direct-applied vegetation index into robotics alone could not provide a trustable result for safe navigation. Therefore, [8] had to combine the vegetation indices with 3D-features given by laser data analysis for a double-check. [1][2] suggested to use an active lighting system to create more independence with different sunshine conditions. Even though the approaches based on vegetation indices perform high accuracy and efficiency, the question regarding to traversability is not yet answered.

In this context, we are going to answer the question of transferability by classifying vegetation into two classes: navigable and non-navigable. For that aim, we first try to figure out which vegetation can be passable for an AVG. For an easier understanding the case, let us start to discriminate between a stand of grass and a roll of barbed wire, or between cornstalks and thin trees. Respecting to the chlorophyll-light spectral synthesis, the more chlorophyll a material has, the easier it is to drive through. Grass and cornstalks contain richer chlorophyll, so they are easier to drive through. This property can be exploited using a multi-spectral approach. Particular in this work, we follow the works of [1] and [8]. On the other hand, regarding to kinematic consideration, grass and cornstalks are easy to drive through because of less resistance. In other words, grass and cornstalks are softer and movable, which can be clearly seen that they are easier to be moved under blowing wind. In order to utilize this characteristic, we suggest to use an air compressor device to create strong wind. The movement of vegetation will be detected and recorded to set levels of "resistance". Overall, vegetation with rich chlorophyll and less resistance should be navigable one, therefrom comes the title double-check of passable vegetation detection.

The structure of the paper is organized as follows: Section II describes how to index vegetation respecting to light spectral reflectance. Section III introduces the system design of our robot while an active way to measure the resistance of vegetation is illustrated in section IV. Experiments and results will be discussed in section V while section VI concludes the work.

## II. Multi-spectral-based Vegetation Detection

### A. Standard Form of Vegetation Index

Similar to the intense reflection of fluorescent light from snow, vegetation reflects strongly in all direction the light in the near-infrared band. On the other hand, the photosynthesis process of chlorophyll inside vegetation requires more light spectral absorption in the red and blue bands. Therefore the ratio of radiances in the near-infrared (NIR) and red bands was used as a measure of vegetation index in the satellite remote sensing field and first introduced by [19].

$$RVI = \frac{\rho_{NIR}}{\rho_{Red}} \tag{1}$$

where $\rho_{NIR}$ and $\rho_{Red}$ are reflectance values in NIR and red bands, respectively. The absolute value of the ratio changes significantly depending on different illumination conditions. Thus, a normalized difference vegetation index (NDVI) was introduced by [21][22], which is now used as a standard form of band ratio for vegetation studies.

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \tag{2}$$

[8] applied this index quite successfully in the field of robotics under good lighting conditions. When considering more illumination effects, the changes in light reflectance in the near-infrared and red bands are not linear, thus, NDVI can not be used efficiently to detect vegetation. Concretely NDVI of pigment metals, dark wet soil or black polymer synthesis materials in many circumstances might be even higher than of vegetation.

### B. Modification Form of Vegetation Index

In order to be stable with respect to illumination effects in outdoor environments, [1] proposed to use a MultiCam which integrates a CMOS sensor and Photo-Mixer Device (PMD) sensor into a molecular set-up [23]. The MultiCam has its own infrared lighting system with the wavelengths centered at 870 nm. The intensity of the lighting source is adjustable, which lets a chance to stabilize the received NIR reflectance values. [1] illustrated that there was a linear proportion of illumination to red but logarithm proportion to NIR. Thus, a better fit of normalized difference vegetation index was devised as follows [1]

$$MNDVI = \frac{\rho_{NIR} - log(\rho_{Red})}{\rho_{NIR} + log(\rho_{Red})} \tag{3}$$

Our previous work [1] has shown that MNDVI performs much better than NDVI in classifying vegetation and non-vegetation under different lighting conditions while taken into account shadow, shining, and overexposure effects. The logarithmic term in **Eq. 3** expresses the less impact of the red reflectance when an artificial lighting system is used. However, the softening red reflectance impact in MNDVI index is presenting problems in applied in an under-exposure or dim lighting condition where the logarithm term approaches to zero. In contrast, NDVI reveals good performance in these circumstances but failed to deal with strong shining and over-exposure effects. Therefore, in this work, we propose a convex combination of both the indices and supposed to be less sensible against illumination changes.

$$VI_{norm} = \alpha \times MNDVI + (1-\alpha) \times NDVI \tag{4}$$

where,

$$\alpha = \begin{cases} 1 & \text{if } RED > T_{expo} \\ 0 & \text{otherwise} \end{cases}$$

$T_{expo}$ is manually set to define the state of dim lighting or under-exposure on the red channel (in our case, $T_{expo} = 0.3$ when the red values are normalized). Thus, the NDVI index is only used in case of under-exposure or dim lighting condition, otherwise vegetation detection relies on the MNDVI index. **Fig. 1** illustrates examples of vegetation detection results based on NDVI, MNDVI and $VI_{norm}$, respectively. The results perform a good supplement between the two forms of vegetation indices against illumination changes. To have a more quantitative persuasion, we provide the confusion matrices of vegetation detection based on different vegetation indices as in **Table I**[1]. Whereby, MNDVI and $VI_{nortm}$ perform better than NDVI. The $VI_{norm}$ index increases the true positive precision rate but also allows more false positive compared with the MNDVI. This issue can be covered when combined with the active method introduced in the next section.

Fig. 1. Example of vegetation detection results given by different vegetation indices. The first column illustrates original images. The second column describes detection results given by the NDVI approach. The third column shows results of MNDVI approach. The last column demonstrates the results from $VI_{norm}$ approach.

[1] *The evaluation was carried out with 500 outdoor images captured in both morning and afternoon conditions*

TABLE I
CONFUSION MATICES OF DIFFERENT VEGETATION INDICES

| | NDVI [21] | | MNDVI [1] | | $VI_{norm}$ (this paper) | |
|---|---|---|---|---|---|---|
| | Vegetation Detection | Non-Vegetation | Vegetation | Non-Vegetation | Vegetation | Non-Vegetation |
| Vegetation | 86.24 | 13.76 | 90.24 | 9.76 | 93.47 | 6.53 |
| Non-Vegetation | 22.51 | 77.49 | 14.38 | 85.62 | 18.32 | 81.69 |

## III. SYSTEM DESIGN

The main configuration in details of our autonomous mobile outdoor robot (AMOR) is described in [1][2][4]. As mentioned in the introduction part, for this particular task, we need a blowing device to create wind to effect vegetation. One might immediately think about utilizing the available air compressor of the robot's air-break system. This, however, is not a reliable solution. The robot lasts his battery quickly because of high power consumption for the charging process of the air compressor. The blowing duration is very short due to the small air compressor tank. More seriously, using the air compressor would affect to the break system, thus, potentially causes an unexpected movement of the robot. Then, we come up with an idea of using independent blowing devices. Take a look at current products for such work, we find Bosch leaf blowers such as Bosch ALB 18 LI Cordless Li-Ion and Bosch ALS 25 which are really suited for the work and quite cheap, at around 80 Euro. Indeed, the leaf blowers can run continuously for 10 minutes at blow speeds of up to 215 km/h. Meanwhile, the robot only needs to turn on the blowing device in case of facing vegetation as obstacle, and for each time the blowing duration required is just from five to ten seconds. Therefore, after each fully charge, the device can be used for at least 60 halt states, which is so far satisfy us at the current stage.

Since the aim is to detect tall grass or branches of leaves which block the path of the robot, our interested area is basically the local one at the front. The goal is to cover the whole area with wind, so many blowing devices should be used. The number of the devices used depends heavily on the size of the robot to ensure that all front obstacles are effected by the wind created by those devices. Also, it would be a waste of money to have more than what is needed. In our case, the robot has 2.5 m long, 1.1 m wide, and 1.8 m high, so we need to use six blowing devices mounted at the middle and two sides of the robot (see **Fig. 2**), at the height around 85 cm. Practical experiments show that the distance of 30 cm from one device to its horizontal neighbor is reasonable for the wide cover. For the high cover, we only need to use other pipes with the heads bending down 30 degrees. It is not necessary to have similar ones with the heads bending up because the robot should not try to drive over obstacles including vegetation with the height more than 1.2 m, which is out of our interest. The diameter of all pipes is 7 cm. The design really meets our aim for the tasks of driving over tall grass and passing though a narrow road with many branches of leaves bending down, which have been the main tasks in European Land Robot Trial (ELROB) since 2007.

Fig. 2. The AMOR model is shown here where six blowing devices corresponding with six pipes are mounted at front of the robot.

## IV. A DOUBLE-CHECK FOR PASSABLE VEGETATION DETECTION

As a general rule, the richer chlorophyll the material has, the easier it is to drive through. Hence, vegetation revealing high values of $VI_{norm}$ tends to be passable. A double-check of passable vegetation detection can be done by considering the resistance property of vegetation with respect to kinematic consideration. For that aim, we implemented an air compressor device to create strong wind to effect vegetation. Actually, the problem given to be solved in this work is that the vehicle gets stuck in a corn field or tall grass area or the path is blocked by a branch of leaves. Now, the vehicle has to decide which way provides less resistance based on detecting passable vegetation. So, in this application domain, the vehicle is in halt state and processing time is not extremely critical. Ideally, background subtraction techniques such as Mean and Covariance [24], Mixture of Gaussians [25], Normalized Block Correlation [28], Temporal Derivative [27], Bayesian Decision [26], Eigen-Background [29] and Wallflower [30] could be directly used to establish a background model for the scene before winded. This leads to detect vegetation as foreground objects when blown by the air compressor device. However, even in the halt state, the vehicle has its own vibration created by the engine as operating, which degrades the quality of those background subtraction techniques. In order to assure a robust motion detection, a motion compensation process is necessary. The following explanation reveals how to compensate the vibration of the vehicle. First, with the high speed of frame rate from the MultiCam, at about 30 fps, we can approximately assume that the movement of objects in the scene is rather slow and has a brightness constancy. Assume that after the small time $\delta t$, the frame is shifted $(\delta x, \delta y)$ and the rotation is $\theta$. If $(x', y')$ is the next stage of $(x, y)$ then,

$$\begin{cases} x' = (x+\delta x)cos\theta + (y+\delta y)sin\theta \\ y' = -(x+\delta x)sin\theta + (y+\delta y)cos\theta \end{cases}$$

with the assumption of small movement, we have

$$\begin{cases} x' \approx x + \delta x + y\theta \\ y' \approx -x\theta + y + \delta y \end{cases}$$

Assume a brightness constancy, so

$$I(x', y', t+\delta t) = I(x, y, t) \tag{5}$$

where, $I(x, y, t)$ is the intensity value of a point at the position $(x, y)$ of the frame taken at the time $t$. $I(x', y', t+\delta t)$ is the point when moved to the position $(x', y')$.

From Taylor Series Expansions,

$$I(x', y', t+\delta t) \approx I(x+\delta x+y\theta, -x\theta+y+\delta y, t+\delta t)$$
$$\approx I(x, y, t+\delta t) + \frac{\partial I}{\partial x}\delta x + \frac{\partial I}{\partial y}\delta y + \frac{\partial I}{\partial x} y\theta - \frac{\partial I}{\partial y} x\theta$$

substitution into **Eq. 5**,

$$I(x', y', t+\delta t) - I(x, y, t) \approx I(x, y, t+\delta t) - I(x, y, t) + \frac{\partial I}{\partial x}\delta x + \frac{\partial I}{\partial y}\delta y + \frac{\partial I}{\partial x} y\theta - \frac{\partial I}{\partial y} x\theta \approx 0$$

or the difference of two adjacent frames can be written as,

$$I(x, y, t+\delta t) - I(x, y, t) = \frac{\partial I}{\partial x}\delta x + \frac{\partial I}{\partial y}\delta y + \frac{\partial I}{\partial x} y\theta - \frac{\partial I}{\partial y} x\theta \approx 0 \tag{6}$$

Solving **Eq. 6** throughout the images using least square fit algorithm, the returned parameters of displacement and rotation help to compensate the vibration of the vehicle. The interesting point is that when the robot stops on a slope, its vibration might be significant whereby the small movement assumption is no more valid. In this case, the estimation given by the above vision-based method is not usable. Therefore, we propose to use the Inertial Measurement Unit (IMU) information as a reference to judge whether the above vision-based motion estimation is trustable. In an untrustable case, the IMU information is used instead of the estimated parameters given by the vision-based, but with more concerning about accumulated noise.

In gerneral, the proposed motion compensation algorithm helps to have a better background subtraction, which has been proved through applying two background subtraction techniques with and without the motion compensation process as demonstrated in **Fig. 3**. A performance comparison between all current background subtraction techniques with and without the motion compensation process might be interesting, we, however, have not yet done it due to our satisfaction with the background subtraction result given by the Mixture of Gaussians.

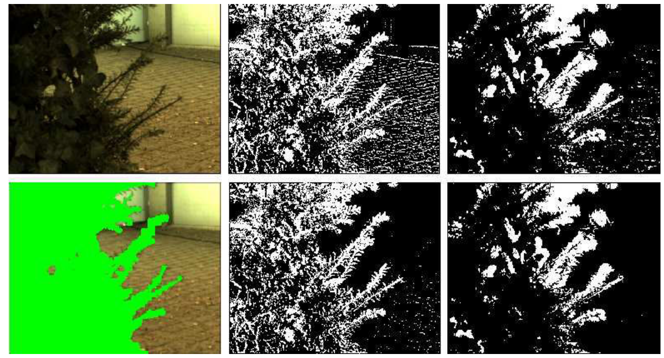

Fig. 3. The first column describes original image and vegetation detection by $VI_{norm}$. The second column shows accumulative background subtraction using Mean & Threshold without and with motion compensation, respectively. The last row illustrates accumulative background subtraction using Mixture of Gaussians without and with motion compensation, respectively.

The problem now is that even we have detected the movement areas in the scene, how should we know which parts are most likely moved significantly? Then, we decide to record all movements of moving pixels in the scene. Look into a local region of the current frame at position $(x, y)$ or look back to **Eq. 5**. We apply another Taylor Series Expansions as follows,

$$I(x', y', t+\delta t) \approx I(x+\delta x+y\theta, -x\theta+y+\delta y, t+\delta t)$$
$$\approx I(x, y, \theta, t) + \frac{\partial I}{\partial x}\delta x + \frac{\partial I}{\partial y}\delta y + \frac{\partial I}{\partial x} y\theta - \frac{\partial I}{\partial y} x\theta + \frac{\partial I}{\partial t}\delta t$$

hence,

$$\frac{\partial I}{\partial x}\delta x + \frac{\partial I}{\partial y}\delta y + \frac{\partial I}{\partial x} y\theta - \frac{\partial I}{\partial y} x\theta + \frac{\partial I}{\partial t}\delta t \approx 0 \tag{7}$$

When already compensated, there should be no consideration in rotation but only local movement of vegetation, so $\theta = 0$. **Eq. 7** is re-written as,

$$\frac{\partial I}{\partial x}\frac{\delta x}{\delta t} + \frac{\partial I}{\partial y}\frac{\delta y}{\delta t} + \frac{\partial I}{\partial t} \approx 0 \tag{8}$$

Or,

$$I_x V_x + I_y V_y \approx -I_t \tag{9}$$

with $I_x, I_y$ are the derivatives, $V_x = \delta x/\delta t$ is the velocity in the horizontal axis, $V_y = \delta y/\delta t$ is the velocity in the vertical axis.

**Eq. 9** is re-written as

$$I_\Delta^T V = -I_t \tag{10}$$

with $I_\Delta^T = [I_x \ I_y]$ and $V^T = [V_x \ V_y]$. **Eq. 10** is such familiar equation expressing the relationship between velocities and derivatives in optical flow problems. The main idea is that the movement of living vegetation is most likely a damped oscillation after a blowing process given by the air compressor device. Therefore, the block diagram of our algorithm is sketched as in **Fig. 4**. Assume that the vehicle captured $M$ frames before and $N$ frames after the blowing process. Background subtraction is carried out and accumulated to result the final accumulative background subtraction, thus, the movement of vegetation should lie in the part marked as foreground (see **Fig. 3**). The masks of the accumulative foreground (MAF) extracted from the final accumulative background subtraction and of detected vegetation (MDV) from $VI_{norm}$ are merged to generate the mask of possible dynamic vegetation(MPDV). The movement of every pixel in the MPDV is recorded by the optical flow process to weight the resistance of those vegetation pixels. Many optical flow algorithms can be applied to record the movements of foreground objects such as in [31], [32], [33], and [35]. Regarding to the particular case of passable vegetation detection, some challenging issues often found in the optical flow problem such as *aperture problem [34], sudden lighting change [30]* are approximately not influential, thus, we propose to use a simple method like dense optical flow [33] to do the work. Also, the work [33] demonstrated that the dense optical flow technique shows out-performance compared with others when taken into account both computation and precision for a two-frame algorithm.

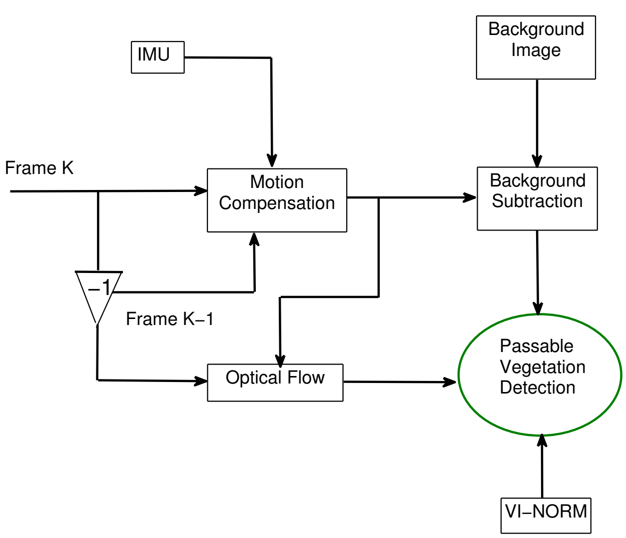


Fig. 4. Block Diagram of the Proposed Algorithm.

## V. Experiments and Results

We used an autonomous ground vehicle with the configuration in details described in [1][2][4] and **Fig. 2** for an evaluation of the proposed algorithm. All data was collected and stored in the robot's computer when the robot traversed throughout outdoor environments in both morning and afternoon conditions. Color images were firstly segmented into small regions with respect to homogeneous color [36]. Whereby vegetation regions were hand-labeled as ground truth to evaluate the outputs of the algorithm. The evaluation in this paper is carried out at region level instead of pixel level. The quantitative evaluation shown in **Table II** is carried

TABLE II
Confusion Matix of Passable Vegetation Detection

| | Passable Vegetation | others |
|---|---|---|
| Passable Vegetation | 98.76 | 1.24 |
| others | 2.01 | 97.99 |

out with 1000 input images captured from 50 halt states of the vehicle (20 frames per each halt state). The result is quite convincing with high accuracy of detecting and weighting passable vegetation, at about 98.37%. Notice that in this work, the vegetation with intense movement after the blowing process is determined as passable vegetation. Thus, vegetation which is not effected by the blowing wind due to far distance to the vehicle or out of the wind flow is detected as non-passable vegetation, which would not be taken into account for evaluating passable vegetation detection. In other words, passable vegetation detection accuracy is only evaluated inside the area effected by the blowing wind. Alternatively, examples of passable vegetation detection are illustrated in **Fig. 5** to have a better intuitive demonstration. Indeed, we can clearly see that branches of leaves and vegetable are successfully detected as passable vegetation, which will be then utilized to enhance decision-making in navigation. One with good observation might recognize that low grass is detected as non-navigable vegetation (marked with dark green) because the movement of low grass is much lesser than of leaves, which is usually confused as the vibration of the robot. It is infeasible to distinguish between the small movement of low grass and the small movement caused by the vibration of the robot even motion compensation already done. However, this issue can be simply resolved by taking the height information into account. Thus, vegetation with low height or less-resistance should be navigable one.

## VI. Conclusions

We have introduced an active way for a double-check of passable vegetation detection, which helps to have a better decision-making in outdoor navigation especially in complex outdoor environments with presence of dense vegetation. Unlike previous approaches in vegetation detection, the proposed approach is not to be significantly affected by visual effects or illumination changes. A double-check between a multi-spectral and an active approaches leads to a more realistic and efficient mechanism for detecting vegetation respecting to the purpose of classifying navigable or non-navigable ones. The approach has been implemented and evaluated in several real-world experiments. The experiments show that our approach is able to accurately detect tall or low grass and branches of leaves with an accuracy of more than 98%. The current approach is limited to detecting and weighting passable vegetation in a halt state of the vehicle. In a future work, we will investigate whether the described approach can also be applied in case of a running vehicle.

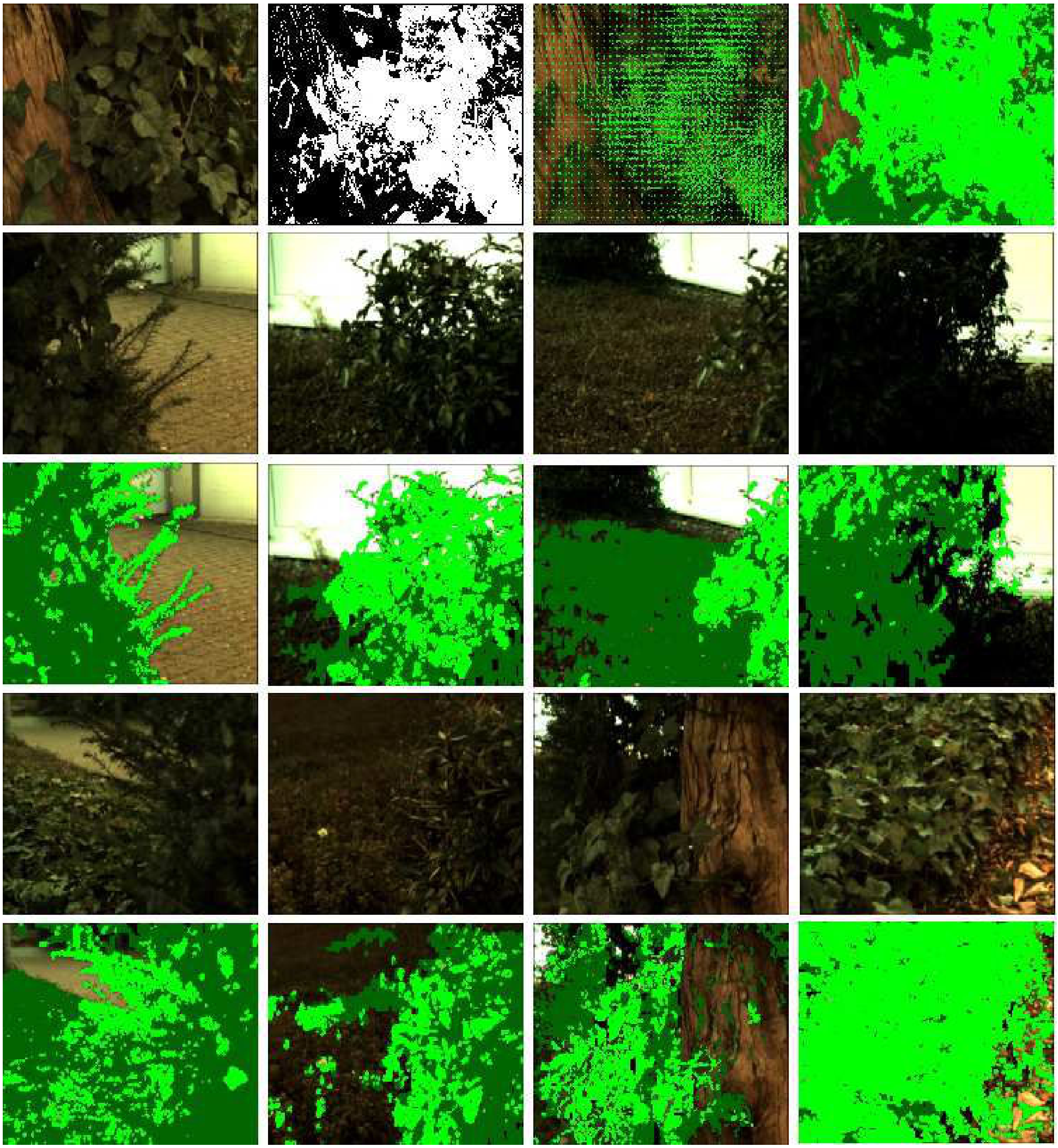

Fig. 5. The first row, from left to right, illustrates original, background subtraction, optical flow and result images, respectively. The second row and fourth row show original images while the third row and the fifth row describe the outputs from our algorithm, respectively. The green and dark green colors reveal passable and non-passable vegetation detected in the result images, respectively.

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