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Improved Optical Flow Estimation In Wrong Way Vehicle Detection

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***Abstract*: Optical flow is the pattern that represents the motion of objects, edges, surfaces in real world by using displacement vectors or color flow. Application of optical flow is used in various problems, especially in traffic monitoring system. The result of optical flow estimation can be used for traffic control, anomaly event detection, vehicle tracking and classification. In this paper, an approach that combines optical flow algorithm and background subtraction with a new method to improve the optical flow in the traffic monitoring system is proposed, followed by a presentation of a system to detect wrong way drivers that takes advantage of the improved flow result. The system has two main stages: in training stage, motion orientation of each lane is learned by analyzing a sequence of flow images. Detecting stage makes use of the orientation model to detect vehicles moving on the wrong direction. Our system has demonstrated successful results.**

Keywords: traffic monitoring system, optical flow, background subtraction, adaptive Gaussian model, directed lane model, wrong way drivers**.**

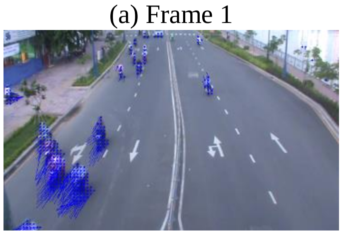
I. Introduction

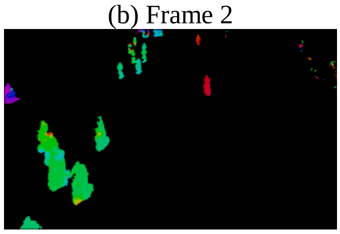
It has been more than 60 years since the first time the concept of optical flow was introduced by American psychologist James J. Gibson [1]. It is the pattern that represents the motion of objects, edges, surfaces in real world by using displacement vectors or color flow based on a color ruler. Nowadays, optical flow estimation has become one of the key topics in computer vision. The task is widely used in many areas such as: motion estimation, object detection and tracking, robot navigation, 3D reconstruction, image registration, etc. One of the most important applications of optical flow is traffic monitoring system, where it serves as the preliminary step of several features including traffic control, vehicle detection and classification, lane detection and anomaly event detection.

Because of such various applications, it is vital to obtain accurate estimation of optical flow. Fundamental differential methods such as Lucas-Kanade [2], [3], Horn-Schunck [4] have been significantly improved by extended methods based on their basic idea such as Farneback [5], [6], Brox's [7], Simple Flow [8], etc. For traffic system, after being utilized in [12], [13], optical flow technique has been combined with background subtraction method to improve the traffic flow estimation in [9]–[11].


(a) Frame 1


(b) Frame 2


(c) Vector flow presentation


(d) Color flow presentation

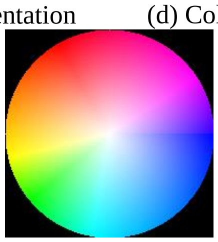

(e) Color ruler

Figure 1. Example of optical flow

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However, traffic flow estimation in developing countries is still challenging due to high traffic density with chaotic scenarios, bad traffic infrastructure, people's lack of complying with traffic laws, etc. One of the problems is the inconsistency in the motion flow throughout each moving object as each of them is supposed to have only one motion direction. This might occur because of many reasons: the particular motions of object parts, the change in light reflection on vehicles, or just because the error in the estimation process.

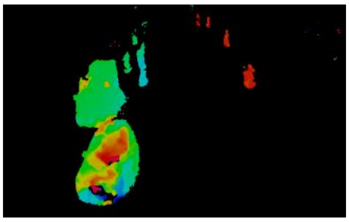


Figure 2. The flow is incorrect as there are different motion directions

In this paper, we present a system to detect wrong way drivers on urban streets, a feature of traffic monitoring system. The system implements our traffic flow estimation approach that includes a new algorithm to solve the mentioned inconsistency problem. It was our previous work in [21]. The main objective of the approach is to estimate the optical flow of urban traffic vehicles using videos from surveillance camera system. The approach consists of three steps. The first step is obtaining the binary foreground using background subtraction process. The second step takes the binary foreground as a mask to extract the moving vehicles from the original frame image for the purpose of forming the color foreground, which is then used as input for the optical flow process to get the traffic flow. The final step carries out the new algorithm to improve the traffic flow result, by identifying moving objects and the dominant motion direction for each of them.

The system has two main stages, both utilizes the improved result from the new approach. In training stage, the motion orientation of the lanes of the street is learned and modeled by analyzing a sequence of flow images. Afterward, detecting stage identifies and marks wrong way drivers in the incoming frames using their flow images and the learned directed lane model.

Beside the improvement in the flow estimation, the system has some advantages. Firstly, with the use of the directed lane model, the system can be applied to not only straight streets but also curved ones with unidentifiable boundaries, which are very common in Vietnam and other developing countries. For comparison, the system in [9] have a pre-processing step, that is, manually defining an observed-region of the street, which we consider impractical because the lanes of the streets are not always straight to identify a trapezium regions. Moreover, it would take lots of effort to setup large camera system. Other systems proposed in [14]–[16] identify the lane boundaries by using Hough Transform technique; however, we found that the texture of objects on the sidewalk area seriously disturbs the result. Secondly, the directed lane model can be customized whether we want to detect violated vehicles on a specific lane or an entire street. Furthermore, it can be included in other tasks of the traffic monitoring system, such as vehicle detection and classification. Finally, the system is vision-based, that is, it only requires video recorded from surveillance camera system, which is affordable and easy in installation as well as maintenance. Therefore, the system is suitable for developing countries, especially in Vietnam since we can make use of the existing cameras that were already installed on the street.

The rest of the paper is organized as follows. In section II there are four subsections. The first subsection gives an overview of the proposed system. In the second subsection, we will describe the approach to obtain the improved traffic flow, which includes the background subtraction step, the optical flow estimation step, and our new method to improve the traffic flow result. The third subsection will present the process to learn the motion orientation of the lanes. The last subsection will present the wrong way vehicles detection process. Experiments will be discussed in section III, followed by the conclusion in section IV.

II. Materials and Methods

A. System Overview

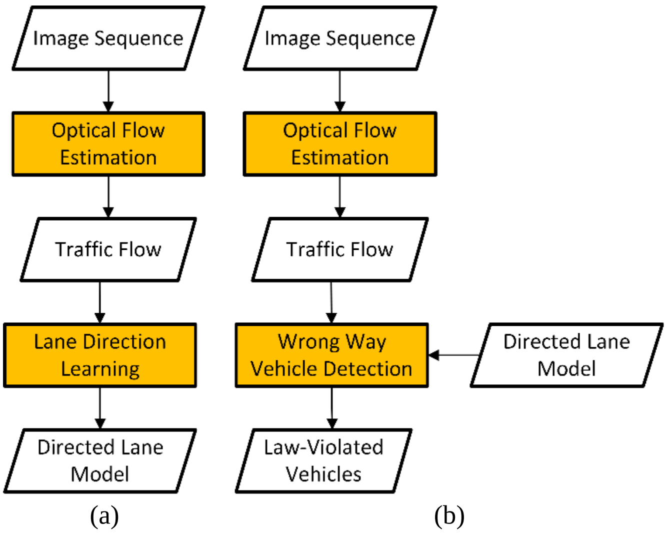


Figure 3. a) Flow chart of directed lane learning stage. b) Flow chart of wrong way vehicle detection stage.

Fig. 3 shows an overview of our proposed system to detect the vehicles circulating in the wrong way. The system is based mainly on two stages. Firstly, in training stage, a sequence of traffic flow images, which are estimated using optical flow method, are analyzed to generate directed lane model. After that, in detecting stage, the traffic flow images of incoming frames of the traffic footage are compared with the learned directed lane model to identify vehicles moving in wrong direction.

B. Improved Optical Flow Estimation

In this section our optical flow approach that aims to solve the problem of the inconsistency of motion direction in each moving object is presented. It follows the typical approach that combines optical flow estimation method with background subtraction method. Nevertheless, we propose a new method to improve the estimated traffic flow at the end of the process. The flow chart of the approach is shown in Fig. 4. Both training stage and detecting stage of the proposed system will benefit from the flow improvement.

1) Background subtraction

(a) Background subtraction using adaptive Gaussian Mixture Model

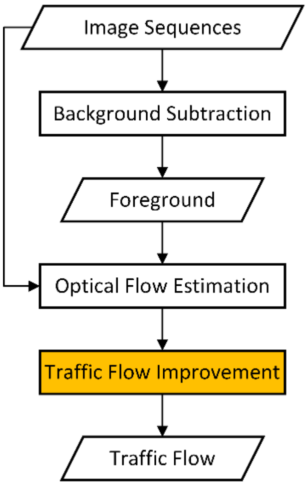


Figure 4. Flow chart of traffic flow estimation approach

Background subtraction is a method for the segmentation of moving regions in image sequences. The algorithm for background subtraction is based on the method proposed by Stauffer and Grimson in [17], then improved by KadewTraKuPong and Bowden in [18] and Zivkovic in [19]. In their approach, each pixel is modeled as a mixture of weighted Gaussian distributions. Different Gaussians are assumed to present different colors. The probability that a certain pixel has the value of x_t at time *t* is defined as:

$$p(x_t) = \sum_{i=1}^{K} w_i \eta(x_t, \mu_i, \sigma_i) \qquad (1)$$

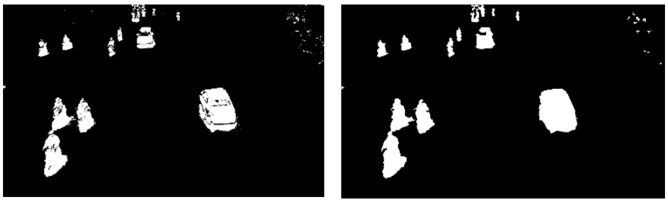
where w_i is the weight of the i^{th} Gaussian component; μ_i is the mean, σ_i is the covariance and $\eta(x_t, \mu_i, \sigma_i)$ is the normal distribution of the i^{th} Gaussian component.

The background components are determined in a heuristic manner as the ones containing the highest probable colors, that is, the colors that stay the longest and least variant in the scene. For the foreground detection, each pixel value is compared with each of the background components' expected value and is classified as foreground if no match is found. In order for the model to be able to adapt with the change in illumination, an online approximation algorithm is applied. The maintenance is made by iteratively update the Gaussian mixtures using new pixel value from incoming frames.

This parametric method has very low memory complexity and deals with critical situations: noise image, camera jitter, camera automatic adjustment, placement of camera, light switch, time of the day, bootstrapping, shadows, slow moving objects…

(a) Input frame (b) Binary foreground image

Figure 5. Background subtraction example



(a) Binary foreground (b) Enhanced binary foreground

Figure 6. Foreground enhancement example

(b) Noise reduction and foreground enhancement

The background subtraction process produces a binary foreground image for each of the input frames. To enhance the results, we perform closing morphological operation on those images. The operation is obtained by the dilation of the image followed by the erosion. Not only does it reduce the noises in the image, but it also fills small holes the foreground regions.

However, larger holes in foreground blobs are still retained. In order to take this further, contour detection technique is applied for the purpose of identifying the contours around the blobs in the binary image. The technique is implemented based on border following algorithm in [20]. We filter out more noises by calculating the area within the contour using Green formula and eliminating the blobs having too small area. After that, we scan and mark every pixels inside the contours as foreground, filling the enclosed holes in the foreground blobs that are left from the closing operation.

This task is important as it will greatly improve the quality of the foreground image. Thus, the results of object identification using foreground mask will be much more accurate.

2) Optical Flow Estimation

(a) Pre-processing

With the binary foreground images used as masks, we compare them with the original frames to extract the color foreground into distinct images. The results then serve as input for optical flow estimation process.

(b) Estimation using Brox's optical flow method

The new improvement method in our approach that we are going to present in later subsection is a supporting algorithm; therefore it can be combined with any dense optical flow estimation method. In this paper we chose Brox's optical flow algorithm as it produces satisfactory results with relatively low error. The paper [7] proposing the algorithm did receive the Longuet-Higgins Best Paper Award in 2004.

Brox's optical flow algorithm estimates the optical flow by using energy functional that combines three assumptions including:

- Grey value constancy assumption: the grey value of the pixel is assumed not to change during the movement.

$$I(x,y,t) = I(x+u, y+v, t+1) \quad (2)$$

- Gradient constancy assumption: the spatial gradient of an image sequence is assumed to remain constant during motion.

$$\nabla I(x,y,t) = \nabla I(x+u, y+v, t+1) \quad (3)$$

- Smoothness assumption: the assumption expresses the interaction between neighboring pixels.

$$|\nabla u|^2 + |\nabla v|^2 = 0 \quad (4)$$

To be able to calculate optical flow for large displacements, this algorithm uses a consistent numerical scheme based on two nested fixed point iterations. The system can be solved using Gauss-Seidel method or SOR method. Also, multi-scale method is applied in the case of slow convergence rate.

(c) Post-processing

With the estimation result in dense optical flow, we need to eliminate incorrect flows in the background areas by comparing with the binary foreground mask. Next, we get rid of outliers by eliminating the motion vectors with unusually large (>30% of image size) or small (<1 pixel) magnitude. The color optical flow is then generated for further process. Since there is a possibility that the videos recorded from different cameras do not have the same frame rate, only motion direction information of the optical flow is used.

3) Traffic Flow Improvement

In this subsection, we present a four-step algorithm to solve the problem of the inconsistency of motion flow throughout a moving object. The basic idea behind this task is to collect motion directions in every pixels of each moving object and determine which one of them is the dominant direction for that object.

Step one, we establish the 16-bin motion direction histograms for the color ruler, each bin represents one cardinal direction class $d_i \in$ *{N, NNE, NE, ENE, E, ESE, SE, SEE, S, SSW, SW, WSW, W, WNW, NW, NNW}*. The direction classes are sorted in clockwise order. The histogram should be uniform so all the bins have the same size.

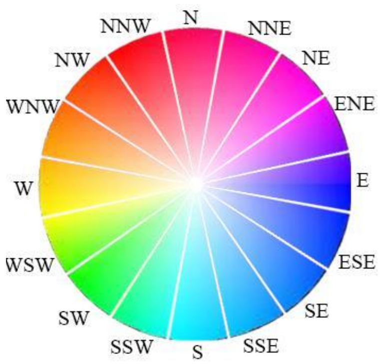


Figure 7. Color ruler with 16-bin motion direction histograms

Step two, we identify the moving objects by applying contour detection technique on the flow image. However, since the technique only works with binary image, we need to convert the color optical flow result to binary type, where each pixel has one of two possible values: 1 if it has a displacement, that is, it belongs to any moving object; 0 if it does not. The contour finding result from the previous application of the technique (subsection A.1.b) should not be reused because it may produce some inaccuracy.

Step three, for each blob, we proceed to calculate the histogram and determine the bin representing the main direction. First, we compute the number of pixels having RGB values that fall in the range of each bin. We define:

- W_{d_i} : the number of pixels having RGB values that belong to the range of bin d_i.
- $\Omega = \{I_1, I_2, ..., I_n\}$: the set of available RGB values
- w_I : the number of pixels having RGB value I.
- $x_{(I,d_i)} = \begin{cases} 1 \text{ if I belongs to bin } d_i \\ 0 \text{ otherwise} \end{cases}$

Hence

$$\forall i \in [1,16], W_{d_i} = \Sigma_{I\in\Omega} w_I x_{(I,d_i)} \quad (5)$$

The binomial filter (1/4, 1/2, 1/4) is then applied for each bin W_{d_i} and its two neighbors $W_{d_{i-1}}, W_{d_{i+1}}$ to take their values into account. This will act like a smoothing technique, which reduces noises in the flow estimation. The bin representing the main direction is the one having the largest final value.

$$W'_{d_i} = \begin{pmatrix} \frac{1}{4} & \frac{1}{2} & \frac{1}{4} \end{pmatrix} . \begin{pmatrix} W_{d_{i-1}} & W_{d_i} & W_{d_{i+1}} \end{pmatrix} \quad (6)$$

$$\mathrm{d}_{\max} = \arg\max_{d_i, i\in[1,16]} W'_{d_i} \quad (7)$$

Step four, we calculate the mean RGB value representing the main motion direction that will then be assigned to pixels of the entire blob. It is defined as the total sum of pixels' RGB values that fall in the range of the main direction bin divided by the number of pixels having RGB values which belong to that bin:

$$I_{mean} = \frac{\Sigma_{I\in\Omega} w_I \, \mathrm{I} \, x_{(I,d_{\max})}}{\Sigma_{I\in\Omega} w_I x_{(I,d_{\max})}} \quad (8)$$

C. Directed Lane Learning (Training Stage)

The estimation of each lane's motion orientation on the image are learned through the analysis of a large amount of frames. In each new frame the optical flow is computed and the color traffic flow is used as input images. A Gaussian mixture model is then applied to learn the motion direction of each pixel in the image. The method is a modified version of background subtraction method which were described in subsection B.1. The difference between the modified method and the original one is the heuristic for determining the pixel's motion direction color. Since the static background of the color traffic flow image is guaranteed to have zero value, the direction of a pixel is decided to be the non-zero color that stay longest in the mixture and the time portion of the pixel staying on scene must be longer than a minimum factor. The factor is defined so that it can rule out noises in the estimation as well as incorrect directions created by violated vehicles. If none of the components satisfies the conditions, the pixel is marked as background and no pixel orientation is assigned.

The sufficient number of frames for the training stage to obtain a correct estimation depends on the number of vehicles circulating on the street. If there are too few or no vehicles circulating in one part of a street, the direction of that part would not be learned.

D. Wrong Way Vehicle Detection (Detecting Stage)

In this subsection it is described the process to detect the vehicle circulating in the wrong ways of the street. The process makes use of the lanes' motion orientation. In each new frame the color traffic flow is generated and then compared with the lane image, pixel by pixel. The pixels in which the difference between the direction of the flow in the present frame and the corresponding direction in the lane motion orientation are larger than a predefined threshold are marked as the ones having wrong direction. Those pixels are then grouped into blobs, which denotes the wrong way vehicles, using contour detection technique. The blobs with too small area will be considered as noises and be filtered out.

Furthermore, in order to increase the accuracy of the detecting stage, an observation zone where the sizes of vehicles do not change significantly between consecutive frames can be defined. The method proposed in [22] identifies the zone by analyzing the rate of change of objects' size at different locations of the image in a series of frames. This will help eliminate areas where the vehicles are far away from the camera, which makes them too small and unclear to be detected.

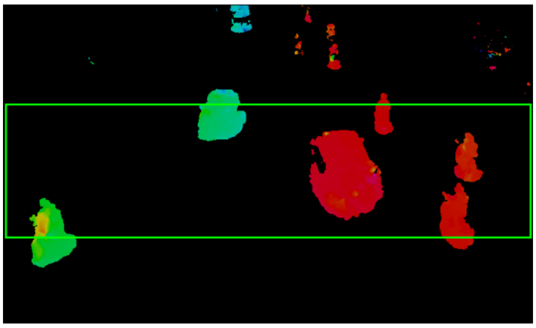


Figure 8. Example of observation zone (between two green lines)

III. Results and Discussion

To evaluate the proposed approach, we performed a number of experiments using frame images that are extracted from actual traffic video footage. The videos were recorded on Vo Van Kiet Street (Sequences VVK1C25_03, VVK2C15_01, VVK3S15_01) and Phan Dang Luu Street (Sequence PDL2), Ho Chi Minh City, Vietnam by camera Sony Handycam DCR-SR68 in resolution 800x480.

The experiments were done on a machine with Intel Core i5 3230M 2.6GHz and 8GB DDR3 RAM. The CPU has 2 cores with Hyper-Threading and Turbo Boost, allowing 4 threads to run simultaneously at 3.0GHz. Also, Brox's Optical Flow method is implemented using NVidia CUDA Runtime API to utilize parallel computing on GPU, so the choice of GPU can affect the performance of the system. The GPU we used on the machine is a NVidia GeForce GT 650M with 384 CUDA cores running at 950MHz, equipped with 4GB of DDR3 VRAM.

The parameters we used for background subtraction with Gaussian mixture model were K = 4, α = 0.025, matching threshold = 2.5, background threshold = 0.6. For Brox's optical flow method, the parameters were scale = 0.8, α = 0.03, γ = 50, inner iterations = 10, outer iterations = 77, solver iterations = 10. For directed lane learning stage, the parameters were K = 4, α = 0.03, matching threshold = 2.5, lane threshold = 0.6.

A. Improved Optical Flow Estimation

1) Comparing the quality

With four pairs of frames from the two video sequences, at first we will compare the results of Brox's method with background subtraction with the results of Brox's method only. After that, we will observe the results of our approach.

As can be seen in Fig. 9 (e)-(h), Brox's method generated results that are incorrect in several regions, especially in the background. Therefore, the estimations are totally unusable. It is because Brox's algorithm is based on the grey value constancy assumption and the gradient constancy assumption; therefore, when the objects have the similar gradient value with another's or with the background's, the flow can be incorrect. The same thing happens with different areas of the road having the same color and gradient. Background subtraction helps eliminate the problem. The results of Brox's method combined with background subtraction in Fig. 9 (i)-(l) are significantly better. The flow directions are generally correct, the moving vehicles are identifiable. Using binary foreground mask, the system can exclude similar gradient values between moving objects and the background. As a result, the chance that the optical flow is incorrect by similar gradient will decrease.

However, there still exists areas where the flows are in the wrong direction. In Fig. 9 (i), it is the car about to move out of the scene; in Fig. 9 (k), they are the moving arms of pedestrians; and in Fig. 9 (l), it is the windshield of a car. That is because the flow estimation was affected by the changes in light reflection from moving vehicles, as well as the particular motions of body parts of the pedestrians. It is the problem with the inconsistency of motion flow throughout a moving object that we described earlier. Our proposed method (Fig. 9 (m)-(p)) corrected those wrong areas by including a new method to determine the main, dominant motion flow of each moving object and then replace the particular motion flows with it. The results are more accurate than the estimations of previous methods, the motion direction of each moving vehicle is consistent.

Nonetheless, the results are still not perfect. Occlusion regions, which are in the first frame but not in the second frame or vice versa, such as a car entering or leaving the scene, can cause error in the motion estimation. The problem was partially fixed by the proposed algorithm; however, more research for proper method is needed.

2) Processing time measurement

We choosed a pair of frame images and resized them to 3 others resolutions: 1280x768, 1800x1080 and 3600x2160. After that, we measured the average runtime of our improvement algorithm with four pairs of frame images. We also measured the average runtime of the whole optical flow estimation task for comparison purpose. As can be seen from Table 5.1, the runtime measurements of the optical flow method are very much longer than those of the proposed algorithm. Therefore, the improvement algorithm can be applied without any performance hit.

Table 1. Optical estimation runtime measurements

Resolution	Improvement algorithm avg. runtime (ms)	Optical flow estimation avg. runtime (ms)	Percentage (%)
800x480	36	1700	**2.12**
1280x768 (~ HD)	77	2742	**2.80**
1800x1080 (~FHD)	171	4304	**3.97**
3600x2160 (~4K)	585	13908	**4.20**

B. Directed Lane Learning

We performed the experiment with three different traffic videos. For each video, a sequence of 1000 traffic flow images were used to form the directed lane model. For comparison, we obtained the background images of the video with the use of background subtraction technique, and then applied Hough Line Transform technique on each of the images to detect the bounding lines of the lanes.

Now we compare the lane results of our method and the results of Hough Line Transform technique. Fig. 10 (d)-(f) show that eventhough the lane models do not span the entire actual lanes, they cover most of the parts where there are vehicles circulating regularly. On the other hand, the Hough Line Transform technique was able to detect the bounding lines of the lanes of straight streets, as can be seen in Fig. 10 (g), (l). However, in the case of curved streets, it failed to do the same thing as the lane boundary is divided into serveral lines (Fig. 10 (k)). The technique also got problems with the texture of fences, houses or trees on the street sidewalk, resulting in unecessary lines which seriously disturb the result.

As can be inferred from the experiment results, the Hough Line Transform technique is more suitable for developed traffic system with well-designed roads and clear color contrast between the road surface and the lane marking. Also, it is more often to apply the technique with video from camera system mounted on cars instead of bird's eye cameras since the sidewalk areas are less visible. On contratry, our lane detecting method produces good results even with urban traffic systems having complicated road design. The most important advantage of our method is that it can determine the motion orientation of the lanes, which can be used as the mask to detect wrong way vehicle. Moreover, the mask is easily customizable if we only need to detect in one specific lane.

C. Wrong Ways Vehicle Detection

Fig. 11 (g)-(i) demonstrate the results in detecting stage. By comparing the directed lane model in Fig. 10 (d) with the improved traffic flow images in Fig. 11 (d)-(f), the wrong way drivers were successfully detected from incoming frames. Fig. 12 (a) shows the frame 1620 extracted from sequence VVK1C25_03 that was put in the detecting stage. With the improved traffic flow image from our method in Fig. 12 (c), the system correctly identified no violated vehicle in the frame (Fig. 12 (e)). However, using the unimproved traffic flow in Fig. 12 (b) to compare with the directed lane model produced incorrect result (Fig. 12 (d)). It is because in the frame image, there is a car about to leave the scene, causing an occluded region in the next frame image, which resulted in an error in the flow image. An incorrect traffic flow led to an incorrect identification of violated vehicle.

IV. Concluding Remarks

In this paper, we presented a system that can effectively detect wrong way drivers on urban streets. In the training stage, the motion orientation of each lane of the street is learned using Gaussian mixture model. The system's detecting stage compares the directed lane model with incoming traffic flow image to identify violated vehicles. The system incorporates an optical flow estimation approach with a new algorithm that can improve the traffic flow by identifying the dominant direction of each moving object. The algorithm eliminates the estimation error caused by particular motions of parts of moving object and light reflection from vehicle. When combined the proposed method with background subtraction method and optical flow estimation, the experiments show promising results. Nevertheless, there is room for improvement as it still lacks occlusion detection and object shadow removal. Moreover, further studies are needed to find a way to detect the obstruction caused by unintended objects in front of the camera and then reconstruct the lost parts of the image.

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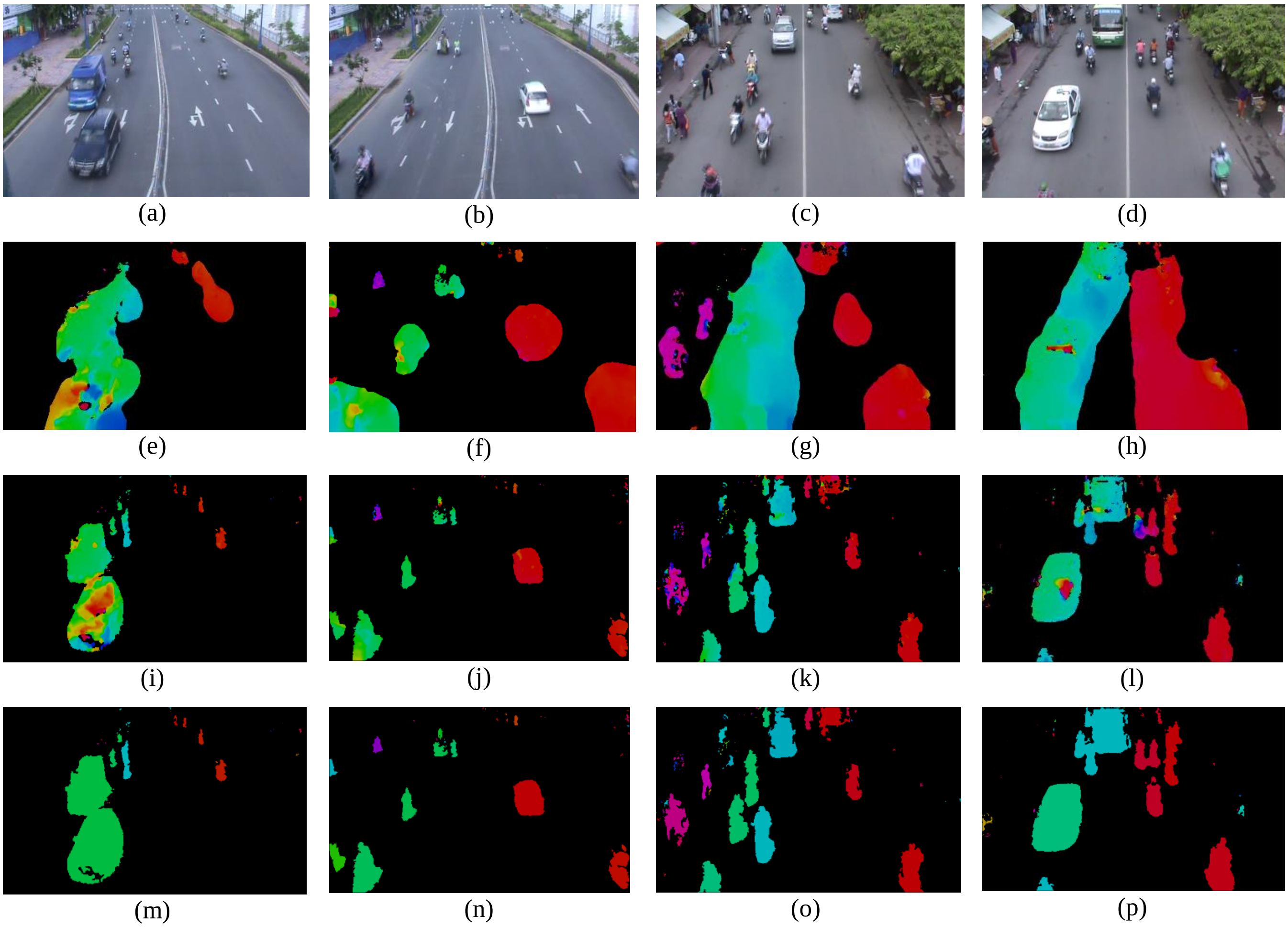

Figure 9. Color flow results of Brox's optical flow estimation without background subtraction (Row 2), with background subtraction (Row 3), with background subtraction and then improved with our method (Row 4). (Row 1) Original frame images. (Column 1) Frame 1910 of sequence VVK1C25_03. (Column 2) Frame 445 of sequence VVK1C25_03. (Column 3) Frame 7275 of sequence PDL2. (Column 4) Frame 7560 of sequence PDL2.

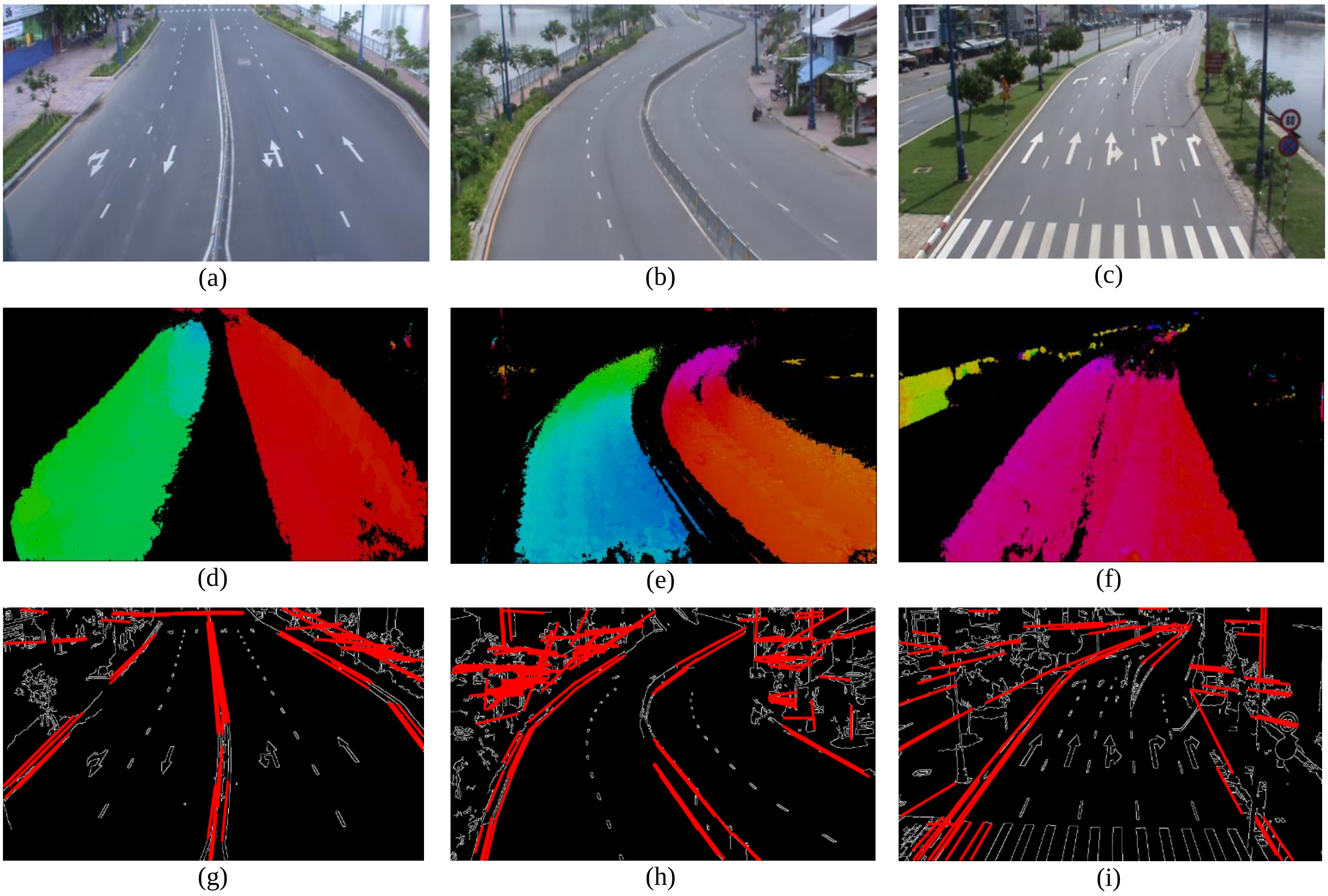

Figure 10. (Row 2) Results of directed lane learning stage. (Row 3) Results of Hough Line Transform technique. (Row 1) Actual street images. (Column 1) Sequence VVK1C25_03. (Column 2) Sequence VVK2C15_01. (Column 1) Sequence VVK3S15_01.

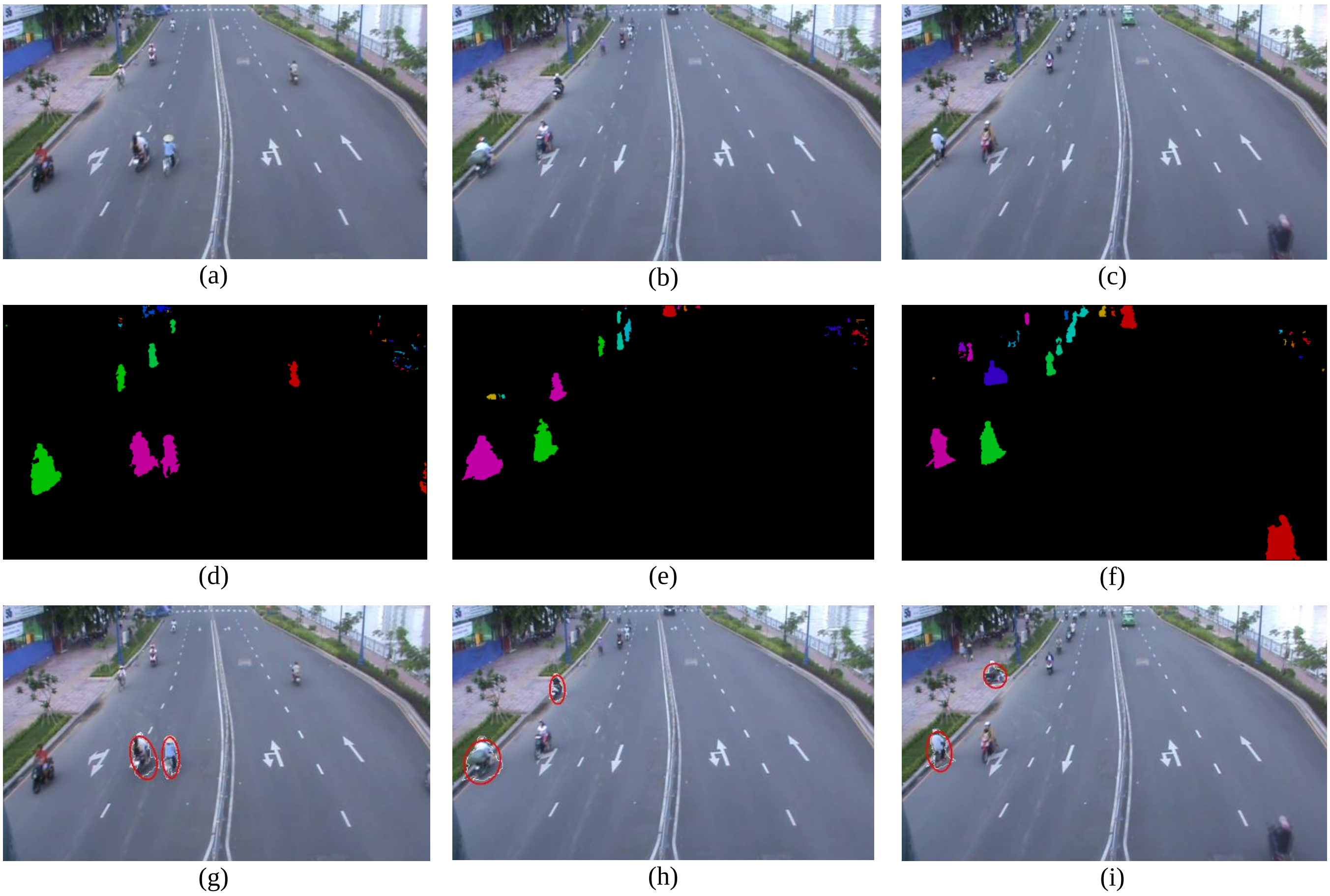

Figure 11. (Row 3) Wrong way vehicle detection results. (Row 1) Original frame images. (Row 2) Traffic flow images. (Column 1) Frame 1205 of sequence VVK1C25_03. (Column 2) Frame 4260 of sequence VVK1C25_03. (Column 3) Frame 8270 of sequence VVK1C25_03.

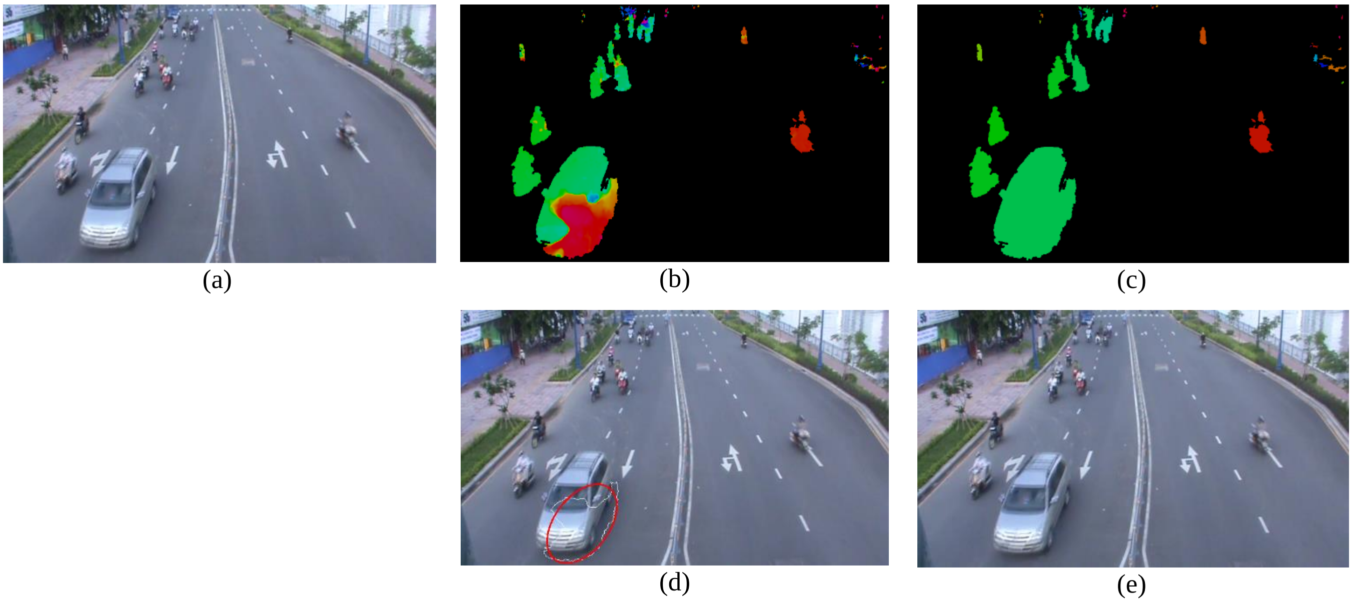

Figure 12. a) Original frame 1620 of sequence VVK1C25_03. b) Unimproved traffic flow image. c) Improved traffic flow image. d) Wrong way vehicle detection result with unimproved traffic flow image. e) Wrong way vehicle detection result with improved traffic flow image.

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