An Obstacle Detection System
Using a Light Stripe Identification Based Method

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Abstract

A light stripe tracking and identification method is proposed for a structured light based obstacle detection system operating in an outdoor environment. The method makes the structured light based detection system more robust and applicable to use outdoors as aid for navigation. The method differentiates between the structured light produced by a light stripe projector and the light stripe kind patterns caused by ambient illumination. The centre of gravity of the segmented light stripe is tracked by using a Kalman filter. The position information together with the other properties of the stripe segment, including intensity, length and orientation are used to identify the same light stripe segment in adjacent images. By using a pulsed light source it is possible to differentiate between true and false light stripes depending on their time of appearance. During the project, a working obstacle detection system for a partly structured outdoor environment was implemented.

1. Introduction

There are several approaches to sensing the environment of a robotic vehicle. The typical methods have utilized a radar principle or passive computer vision methods, such as stereo vision [1],[6],[8],[4],[3]. Depending on the application, these methods are feasible when the environment is suitable and the speed of the vehicle is low. When the speed of the vehicle increases and the environment is more demanding, more efficiency and reliability are required from the sensory system.With active sensing, the calibration problems and computational costs inherent in passive techniques, such as stereo, can be eliminated.

The advantages of using a light stripe based method for environment sensing are that the resulting method can be fast, accurate and simple. The range of multiple points on the target surface can be measured simultaneously and quickly. In good circumstances, structured light can be used to extract 3-D information from the target [2]. Difficulties might arise in exceptional environment circumstances such as snowfall, fog, bright sunshine or uneven ground.

A ranging system based on structured light is applicable to detecting an obstacle, and can be reliable in favorable circumstances When the circumstances are more difficult, disturbances arise which affect the operation of the system. If these disturbances cannot be eliminated, they may cause false inferences about the environment.

The disturbing effects of ambient illumination constitute one of the main problems in using a structured lighting based range measurement system in an outdoor environment. This paper addresses the applicability of the light stripe tracking and identification based disturbance filtering method for structured lighting based obstacle detection system working in partly structured outdoor environment such as harbor areas.

In this method, the light stripe kind patterns are extracted in real time from a sequence of sensor images. The patterns are segmented and traced while they move in sensor images during vehicle motion. By pulsing the projected light pattern, it is possible to extract those patterns which appear only when the projector is on and, respectively, those which do not follow the status of the light source. This enables differentiation between the projected structured light and disturbances caused by ambient light sources.

2. Perception system

The operating principle of a structured light based obstacle avoidance system is presented in Fig. 1 [5]. The main components of the system are the sensor and the light stripe projector. When the working machine moves forward, the sheet of light sweeps the ground ahead of the machine and possible obstacles lying there. The sensor detects the light-profile reflected from the obstacle.

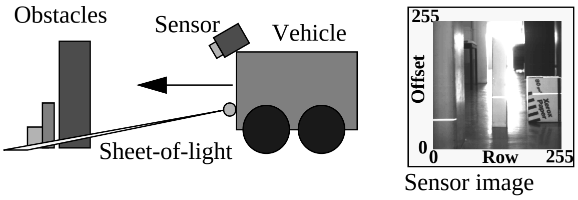

Figure 1. Structured light based obstacle detection system.

When the mutual geometry of the sensor and the light stripe projector is known, based on the image coordinates of the reflected obstacle profile, the range coordinates of the stripe points can be defined and the location of the obstacle determined accordingly.When the system has detected an obstacle, its location is defined and the information passed on to the control system of the machine [7]. The machine can use the location information in different ways; the vehicle can be guided around the obstacle, stopped before collision or guided near to the obstacle for further instructions. The system may also warn the driver of humans crossing the path of the machine.

3. Extracting range profile

Extraction of the range profile is done on a column basis; from every sensor column local maxima that resemble the cross-section of the light stripe are sought. Every column is divided into separate regions, and for every region inside the column only the most promising intensity maximum is selected. If multiple local intensity maxima are found inside the region, the most promising maximum is the one which gets the largest value of quality Q defined by equation

$$Q = (i_{peak} - i_{av}) / w_{peak} \qquad (1)$$

where *ipeak* is the peak intensity of the local maximum, *iav* is the average intensity of the pixels around the peak and *wpeak* is the width of the peak in pixels. Even when the best peak within the region cannot satisfy the predefined thresholds for minimum peak intensity and quality, the peak is not rejected immediately. Instead, it can be accepted as a valid rangel in the stripe segmentation phase if it gets support from neighboring peaks with acceptable quality. When the peak is validated in this manner, it can be used further to validate a possible weak peak in its own neighborhood. This makes it also possible to extract the weak parts of the stripe segments, which makes the stripes more stable for tracking and identification purposes. The stripe extraction principle is shown in Fig. 2.

In the segmentation phase the selected peaks are segmented into straight lines using the LS method. The position of the centre of gravity and the transformed properties; intensity, length and orientation for each stripe segment, are saved. The value of the property *pi* is transformed into the value *Pi* using the equation

$$P_i = sgn(p_i)\sqrt{a_i|p_i|} \ , \quad i = 0,..,N\text{-}1 \qquad (2)$$

where *pi* is the measured value of the property *i* (i.e average intensity of the stripe segment), *ai* is a scaling constant and *Pi* is the transformed value for property *i*. This transformation is done to make the properties more stable for tracking and identification purposes. The properties of the stripe segment in image *k* together with its position define the segment property vector

$$s(k) = \left[P_{int}(k)\ P_l(k)\ P_o(k)\ x(k)\ y(k)\right]^T$$

where *Pint(k)* is intensity, $P_l(k)$ is length, *Po(k)* is orientation and *x* and *y* are the image coordinates of the centre of gravity of the stripe segment.

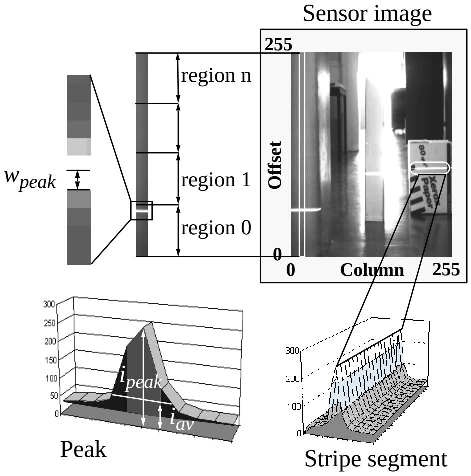

Figure 2. Extracting light stripes from the sensor image

While the extracted and segmented light stripes move in the image sequence, as shown in Fig. 3, they are traced using *trackers*. For each new light stripe segment found in the sensor image *k*, one tracker is created. When a tracker is created, the property vector of the tracker

$$\mathbf{t}(k) = \left[P_{int}(k)\ P_l(k)\ P_o(k)\ x(k)\ y(k)\right]^T$$

inherits the position and properties of the segment shown in Fig. 4, so that $\mathbf{t}(k) = \mathbf{s}(k)$. After initialization, the tracker continuously tries to follow the segment in a spatial domain using the Kalman filter so that the property vector for the next image is

$$\mathbf{t}(l|k) = \left[P_{int}(k)\ P_l(k)\ P_o(k)\ \hat{x}(l|k)\ \hat{y}(l|k)\right]^T \qquad (3)$$

where $l = k+1$.

When light stripe segments are extracted from the image $k+1$, the correct tracker-segment pair is found by using the euclidean distance between the given $\mathbf{t}(k+1|k)_n$, $n = 0,1,..,N-1$, and $\mathbf{s}(k+1)_i$ as a criterion of success, so that

$$min\left\|\mathbf{t}(k+1|k)_n - \mathbf{s}_{available}(k+1)_i\right\| \le d,\ i = 0,1,..,I-1 \quad (4)$$

where d is the predefined distance threshold, I is the number of extracted stripe segments in image $k+1$. N is the number of valid trackers. If the tracker cannot have the nearest segment because it is reserved by another tracker that is closer to that segment, the tracker accepts the *nearest available* segment. When the correct tracker-segment pair is found, a new estimate for the property vector is defined by

$$\mathbf{t}(l|l) = \left[P_{int}(l)\ P_l(l)\ P_o(l)\ \hat{x}(l|l)\ \hat{y}(l|l)\right]^T \quad (5)$$

where $l = k+1$. Because N is usually different from I and sometimes there are no segments within distance d there is usually extra trackers or segments. If there are extra segments, a new tracker is created for those segments. For each extra tracker, its *miss counter* is incremented and if the counter value exceeds the predefined threshold for the counter value, the tracker is removed.

Tracker status is updated every time the tracker-segment pair search is finished. Tracker status shows how many times a tracker has failed or succeeded to find the valid segment and what was the status of the structured light projector when failure or success occurred. The status information of the tracker is used to decide whether the traced segment is generated by the structured light or ambient illumination. The most simple rule is to reject the segments whose tracker status indicates, that during a given time period the segment has appeared although the light source has been switched off.

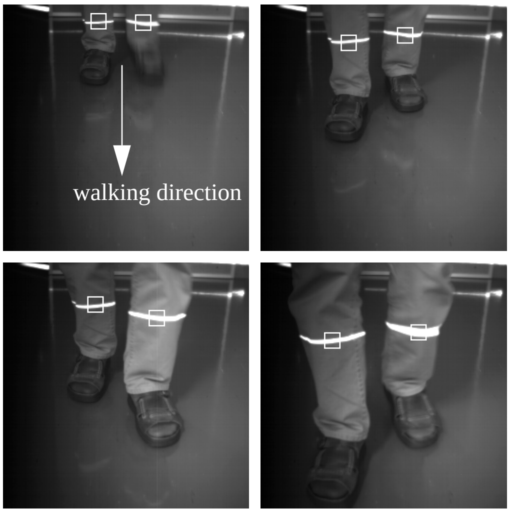

Figure 3. Part of an image sequence. A person is approaching the obstacle detection system.

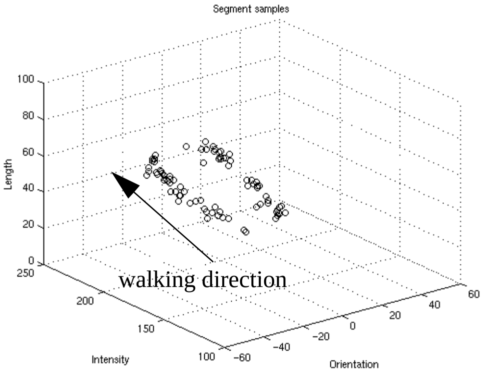

Figure 4. Properties of the two valid segments in Fig. 3.

4. Position tracking

The centre of gravity of the stripe segment is tracked by using the Kalman filter. The state model used in this application is presented below. The matrices used with this model are:

$$\Phi = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix},\ H = \begin{bmatrix} 1 \\ 0 \end{bmatrix}^T,\ \Gamma = \begin{bmatrix} T^2/2 \\ 1 \end{bmatrix},\ x = \begin{bmatrix} position \\ velocity \end{bmatrix} \quad (6)$$

where x is the state vector, Φ is the state transition matrix and H is the observation matrix. Γ models the uncertainty of the process model. Sampling time $T = 1$. In this work, two independent and identical filters were used, one for the x-coordinate of the segment and one for the y-coordinate of the segment.

Kalman filter is the mean squared filtered estimation of $x(k+1)$. The estimate of $x(k+1)$ is

$$\hat{x}(l|l) = \hat{x}(l|k) + K(l)\tilde{z}(l|k) \quad (7)$$

where $l = k+1$ and

$$K(l) = \quad (8)$$

$$P(l|k)H^T(l)[H(l)P(l|k)H^T(l) + R(l)]^{-1}$$

is the Kalman gain matrix and

$$\tilde{z}(l|k) = z(l) - H(l)\hat{x}(l|k) \quad (9)$$

is the innovation process - the new information brought to the system, where $z(l)$ is the measurement (i.e x-or y-coordinate of the segment) at time instant $l = k+1$. The prediction equations are

$$\hat{x}(l|k) = \Phi(l|k)\hat{x}(k|k) \quad (10)$$

and

$$P(l|k) =$$

$$\Phi(l|k)P(k|k)\Phi^T(l|k) + \Gamma(l|k)Q(l)\Gamma^T(l|k) \quad (11)$$

The correction (update) equations are

$$\hat{x}(k+1|k+1) = \hat{x}(k+1|k) + K(k+1)\tilde{z}(k+1|k) \qquad (12)$$

$$P(k+1|k+1) = [I - K(k+1)H(k+1)]P(k+1|k) \qquad (13)$$

From the state transition matrix Φ in Eq. 10 we can see that when prediction for the next state $\hat{x}(k+1|k)$ is done, we have:

$$\begin{aligned} &\text{predicted position} = \text{current position} + \text{velocity} \times T \\ &\text{predicted velocity} = \text{current velocity} \end{aligned} \qquad (14)$$

From the observation matrix H in Eq. 9 we can see that the innovation process is based on measurements made on the position of the centre of gravity of the segment. The initial state covariance matrix is

$$P(0|0) = \begin{bmatrix} \sigma_v^2 & \sigma_v^2/T \\ \sigma_v^2/T & 2\sigma_v^2/T^2 \end{bmatrix} \qquad (15)$$

The state noise variance $Q(k) = \sigma_w^2$ and the measurement noise variance $R(k) = \sigma_v^2$ were chosen empirically.

5. System prototype

The main components of the obstacle detection prototype system were: MAPP2200 Camera [9] by Integrated Vision Products with an interference filter, a 50mW/780nm light stripe projector with a cylindrical lens and a Pentium PC. The performance of the system is good when the operating environment is not illuminated by direct sun light. Figure [5] shows a typical outdoor test situation, where the system detects two obstacles: a container on the left and a wall on the right. The box in the image has been detected earlier. The light stripe identification based filtering method works well when the image frequency is high enough compared to the vehicle speed and the light stripe kind patterns caused by the ambient illumination are stable enough.The speed of the system varies, depending on the parameters used, and is typically 12-40 range profiles/second. If the environment is illuminated by direct sunlight, the dynamics of the sensor should be better and the output power of the light stripe projector should be higher for more reliable operation

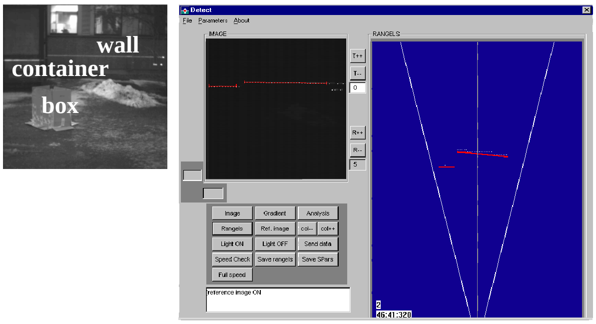

Figure 5. Outdoor test situation. *Left*: Sensor view. *Right*: Response by the system.

6. Conclusion

The purpose of this work was to study the applicability of a light stripe identification based disturbance filtering method for a structured light based obstacle detection system operating in an outdoor environment. The working prototype was implemented and preliminary outdoor tests were carried out successfully. The system was able to operate in real time. The most significant problem in implementing the system was to eliminate the effect of ambient illumination. The method studied in this paper successfully eliminated the effects of ambient light sources, when the system was operating in partly structured environment where the properties of the light stripe segments are usually stable and easy to track. When environment was very complex, the stripe segments became numerous and very short in length and were therefore unstable and hard to track, which sometimes caused false alarms. This problem could be avoided by using a higher image frequency and more effective optics. However, the optics should be chosen so as to keep the field of view large enough for the particular application. Also, there is still some problems due to bright daylight and abrupt shaking of the working machine.

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8. References

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