

## **Automated Detection, Tracking, and Recognition of Roadway Signs**

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## INTRODUCTION

Roadway signs represent a substantial investment of public money in road and highway infrastructure. Their importance in regulating and control traffic, and providing conveniences to travelers is well recognized. In addition, many of the signs provide vital information to drivers for their safety. Studying of Right-of-Way (ROW) images is a cost-effective alternative to field trip survey of the road sign inventory. Traditionally, many highway agencies do not have comprehensive databases on the location and condition of various traffic signs. Some of them have visual information of ROW through the use of film, tape, and more recently, digital images. The sign information contained in these media are normally not recognized nor identified. The applicability of asset management with the visual data is limited.

In recent years, some of highway agencies in the US have been conducting sign inventory as part of their asset management program. Particularly, when sign data is coupled with location information through the use of Distance Measurement Instrument (DMI) and differential Global Positioning System (GPS) receiver, a comprehensive sign inventory can be established relative to sign content, sign condition, and sign positioning with the resolution scale of one to several meters. With precision Inertial Navigation System (INS), positioning information with the accuracy of centimeters is possible. In addition, size dimensioning of signs is also a part of the sign inventory. The applications of automated sign inventory include technologies from Lambda Tech, Transmap Corp. and Geo-3D Corp.

However, the current level of automation in sign identification and recognition, size dimensioning of sign, and location identification is not satisfactory. As a matter of fact, a process of elaborate manual intervention is required. For example, current practice in automated sign inventory is that sign objects in ROW images are detected interactively by user with a computer after surveyed ROW data is downloaded into office computer. This is a tedious procedure considering there are a large amount of video frames, various types of the road signs, and other objects.

As sign identification and recognition is a critical component of automated sign inventory, this paper targets the development of feature extraction and tracking techniques of road signs in ROW images. The purpose is to improve the automation level of sign inventory. A framework of combining the conventional image processing methods with the Kalman filter tracking method is applied to improve the accuracy and efficiency of the ROW image processing. Through the tracking technique, the candidate region of the road sign in the picture can be predicted based on the previous image frame. By using image processing in the proximity of the candidate region of a sign, detection efficiency and accuracy of the sign can be improved. In addition, through candidate regions, integrity of a single sign can be maintained so that multiple signs can be separately tracked in the a sequence of image frames. The methodologies described in the paper fit a dynamic and motion environment, appropriate for a highway survey vehicle. Even though the paper does not address comprehensive techniques for automated sign inventory, the imaging and tracking techniques presented in the paper form a basis for future research in other features in sign inventory, such as size dimensioning.

## LITERATURE REVIEW

Recognizing road sign from the ROW images have been studied for some time. Earlier studies focused on the image processing of the still ROW images. Common techniques for detecting and recognizing road signs are algorithms based on color information and shape information (1 and 12), template matching (1, 2, and 3), and techniques of Neural Network (4, 5, and 6). Color is a dominant feature of road sign. Color segmentation is a frequently used method for the initial detection of signs. The three color spaces, RGB, are the most intuitive since they can be easily extracted from digital images. Some people prefer to using information on Hue, Saturation, and Value (HSV) since they are invariant to lighting conditions (6 and 7). Another advantage of this method is: HSV uses a single hue value while RGB has 3 values. Therefore, the former is easier to be used to find the threshold value and segment the interested object from the background. The drawback is that hue is not suited for gray-level segmentation since it has a constant value along the “gray value” axis. Moreover, small perturbation in RGB signals may cause large variations in the hue (6). Recently, a new color model, CIECAM97, is getting popular because of its illuminance-invariant properties (8). It is said to be similar to human visual perception of mechanisms of colors. Specific shape of the road sign is another property used to detect signs. This technique includes aspect ratio (6), edge detection (1, 4, and 9) and corner detection (5).

However, these algorithms have some limitations. Basic information like color and shape can cause false detection. This is due to wide variety of real world conditions under which the vehicle may come to a road sign. For example, the background of a road sign in downtown area can be very complex and have many road sign look likes. In addition, the quality of a road sign picture can be poor due to light condition, the camera focus, and other factors. It is difficult to develop an imaging system with fixed parameters and algorithms that would perform reliably in dynamic environments, where conditions under which data are acquired are not controllable, particularly factors such as lighting intensity and direction of light may not be favorable. This is a primary reason why existing application of automated sign inventory requires substantial human interaction.

For example, traditional methods based on imaging processing would search road sign in every image frame. This method costs too much computing resources and is therefore too expensive for the real time, or high speed processing. In addition, there may be many road signs in one image frame, resulting in need of extremely robust and sophisticated searching and matching algorithms. Furthermore, if the identity of the same sign in several sequential image frames is not properly tracked, it can be incorrectly recognized as different signs (7). Therefore, in this paper tracking technique is investigated as a solution to the problem of improving reliability of sign detection, and computing efficiency of algorithm implementation.

So far, only a few publications addressed algorithms of using tracking technique in the road sign detection. Fleischer et al. (10) used a model-based, top down approach. Predictions are made of locations in which signs may appear, and shape, size, and color are used to specify edge model for the signs in the 3D world. Signs that are found are tracked through subsequent images using a Kalman filter. Another study focusing on sign detection in cluttered environments is that of Fang et al. (7). Neural networks are used to locate regions that may be the center of signs. Both color and shape features are used. Candidate signs are tracked through time using a Kalman filter. Signs are verified by a set of rules concerning the colors and shapes of the regions. However, the stability of the Kalman model in (7) is not verified because the formation of the transition matrix has a trend to be ill conditioned. In addition, both of (7) and (10) focus on the automated navigation and driving. The model presented in this paper is specifically designed for automated sign inventory, which has additional requirements, such as condition survey of signs and dimensioning of signs. However, the underlying algorithms for automated sign inventory may be used in the field of Intelligent Transportation Systems (ITS).

## **SOLUTION METHODOLOGY**

This paper proposes a framework that can incrementally detect road signs from a sequence of digital video frames. The proposed framework takes full advantage of camera geometrical relationships in video sequences as well as Kalman filter based tracking. The relationship between frames is used to predict the candidate road sign region in next frame. This approach provides more robust and efficient recognition of the road sign. Specially, it differentiates various road signs in one right-of-way picture. The application scenario is that a video camera is mounted on a moving vehicle to capture the right-of-way scene in the front of the vehicle. Once a road sign enters the scene, the sign first begins as a small, undetectable object. Then the size of the road sign increases as the camera move toward the sign. The road sign starts to be detected by the system when the size is increased to a threshold value. Normally more than one candidate region will be found in one frame. It is a computing intensive process to detect a road sign in each frame based on traditional image processing. In our research, a Kalman filter is activated once a candidate region is detected. The application of Kalman filter is to predict the location and size of the candidate region in future frames. This tremendously reduces searching area in images, and decreases searching time. The sign target is tracked until it is big enough to do the micro-scan recognition which is primarily accomplished by template matching. Through tracking, false candidates will be excluded when the candidate region is big enough to be recognized and the different road signs can be tracked and detected separately. The color and shape properties are used to search for the candidate regions initially during the first step. The template matching is used to recognize the road sign when the candidate region is large enough and distinctive.

The general algorithms of the framework are as follows. 1) Detect the candidate road sign region with specific color threshold and geometrical properties of shape. 2) Track the candidate region of road sign and predict the potential region in the following frame using a Kalman filter. 3) Micro-scan the predicted

region by image processing when the region is big enough and distinctive. 4) GPS positioning of the road sign. Figure 1 shows the framework of the system.

### **Candidate region detection**

The first step is a process of coarse searching. The requirement for the detection algorithm is not demanding. The goal of this step is to find all possible road sign regions in each frame. To be marked as a candidate region, it has to meet two criteria. First, the region is the same as or little bigger than a threshold size. Secondly, the result of color and shape analysis shows the possibility of being a road sign. A road sign normally first appears as a small object which progressively increases in size as the vehicle approaches it. Setting the threshold size is to activate algorithms for the road sign detection when the signs are large enough, and therefore reducing the computing resources. Threshold size in this test is set to be  $12 \times 12$  pixel. The road sign look-likes smaller than  $12 \times 12$  in any images are ignored. This threshold value is empirical at this time, and is found adequate in a moderately configured computer system.

Road signs have specific color, for example, the warning signs are yellow, the construction area signs are orange, and control signs are red. Signs have specific shape properties such as square, triangular or circular. The detection process consists of two parts. The first part is image color filtering. The identification of the color requires the color invariant with respect to various view environment and light condition. HSV is used over RGB for this purpose (6). The second part is image smoothing for detecting sign shape. A difficulty in detecting a road sign by shape is that images after color filtering are always fragmented. A simple technique used in the research is processing image by dilating followed by shrinking. Road signs always contain some text or simple symbols in an easily recognizable shape with one background color. Dilating followed by shrinking would generate a solid blob and make the detection easier. Figure 2 shows the images before and after the application of dilation and shrinking. As shown in the figure, road sign region is easily detected since the region becomes a blob with a standard shape. Based on various tests conducted for the research, this technique works well when it is combined with specific color criteria of road sign, and it even works better when the sign is tracked.

### **Kalman filter tracking**

To improve the efficiency of detection process while maintaining a low false hit rate, the technique of Kalman filtering is used to predict road sign by camera geometry information. By applying this technique, the detection process can significantly narrow down the search space for each frame and therefore reduce a large number of false hits which may occur in the case of using traditional image processing for each single frame.

First, a road sign is determined in the current frame, which is accomplished in the previous step of candidate region detection. By computing the geometric relationship of the road sign between adjacent frames, the framework finds the candidate region for the road sign in the next frame. At this time, the image processing step analyzes the candidate region in detail.

It is assumed that the optical axis of the camera is roughly horizontal and the motion of the camera is going along its optical axis. This assumption is often true in the real world settings. Particularly, a camera is mounted on the vehicle and its optical axis is calibrated to be parallel to the horizontal plane of the vehicle. Figure 3a) shows the side view of such scenario and b) illustrates the spatial constraints among road sign planes, image planes and the camera between two successive frames.

The Kalman filter technique includes two phases: time update and measurement update (13). The time update procedure is based on the dynamic equation which is derived from the spatial constraints from the two successive frames. The measurement update is based on the image processing location in the proximity of the predicted candidate region.

As shown in the Fig. 3, camera coordinate system at time  $t_0$  is taken as the basic coordinate system, Z-axis is the camera optical axis and the X-axis is parallel to the vehicle's horizontal plane.  $f$  is the camera focus length. The camera moves the distance  $d$  in the traveling direction, which is measured from the on-board DMI.

With the information of spatial constraints between two successive frames, candidate region size of road sign and its location in the following frame are predicted by a Kalman filter based on the current frame.

Fang et al. (7) provided a modeling example using Kalman filter. However, the validity of the formation of the transition matrix is not suitable for our application. Particularly, stability problem generated by the inverse of ill-conditional matrix may arise. The modified technique in our research has overcome this problem as discussed in the following derivations:

Road sign size prediction:

Assume  $h$  is the actual height of the road sign,  $h_0, h_1$  are the heights of the road sign in two successive frames shown in Fig. 3b). Based on triangular principle, the relationship can be found as

$$h_1 = \frac{1}{1 - \frac{dh_0}{hf}} \cdot h_0 \dots\dots\dots (1)$$

$$w_1 = \frac{1}{1 - \frac{dw_0}{wf}} \cdot w_0 \dots\dots\dots (2)$$

Road sign location prediction:

Assume  $(x_0, y_0), (x_1, y_1)$  are the centroid of the road sign in two successive frames. Since

$$\frac{y_1}{y_0} = \frac{L}{L-d} = \frac{h_1}{h_0} \dots\dots\dots (3)$$

The relationship can be formed as:

$$y_1 = \frac{1}{1 - \frac{dh_0}{hf}} \cdot y_0 \dots\dots\dots (4)$$

Similarly

$$x_1 = \frac{1}{1 - \frac{dw_0}{wf}} x_0 \dots\dots\dots (5)$$

Here,  $x, y, h, d,$  and  $f$  are constants. Based on the above relationships, the dynamic equation of the model is constructed as follows.

The five equations for Kalman filter model (13) are:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1} \dots\dots\dots (6)$$

$$P_k^- = AP_{k-1}A^T + Q \dots\dots\dots (7)$$

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \dots\dots\dots (8)$$

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - H\hat{x}_k^-) \dots\dots\dots (9)$$

$$P_k = (I - K_k H)P_k^- \dots\dots\dots (10)$$

Whereas:

$\hat{x}_k^-$  : a priori state estimate at step k with given knowledge from step  $k - 1$

$\hat{x}_k$  : a posteriori state estimate at step k given measurement  $z_k$

$P_k^-$  : a priori estimate error covariance

$P_k$  : a posteriori estimate error covariance

The parameters here are designed as:

The properties of the road sign in the successive frames at each time instance (frame) can be characterized by its position and size. Let  $(x_t, y_t, h_t, w_t)$  represent the road sign pixels position (its centroid) and size at time t. The state vector at time t can therefore be represented as  $x = (x_t, y_t, h_t, w_t)^T$ . The system can therefore be modeled as

$$x_t = Ax_{t-1} + \omega_t \dots\dots\dots (11)$$

where  $\omega_t$  represents system perturbation which comes from the drive direction variance, DMI measurement error, etc. It is further assumed that the image processing estimates

$$z_t = Hx_t + v_t \dots\dots\dots (12)$$

where  $v_t$  represents measurement uncertainty. Specifically, the position of the current frame t is estimated based on an image processing in the neighborhood of the predicted position (based on the system model). In this manner, the state vector  $x_t$ , along with its covariance matrix  $P_t$ , can be updated using the system model (for prediction) and measurement model (for updating). However, the test conducted in the research shows that the noise of the location state  $[x_t, y_t]$  is much higher than the size state  $[h_t, w_t]$ . On the other hand, the smaller dimension matrix will have lower possibility to be ill conditioned. Due to these two reasons, the state vector  $x = (x_t, y_t, h_t, w_t)^T$  is split into two state vectors:

$$\text{the location state } X = \begin{bmatrix} x_t \\ y_t \end{bmatrix} \dots\dots\dots (13)$$

$$\text{the size state } Y = \begin{bmatrix} h_t \\ w_t \end{bmatrix} \dots\dots\dots (14)$$

The calculation of the Kalman filter includes an inverse of the combination of transition matrix A in the middle. The split of the state vector has improved the stability of the model because it replaces the  $4 \times 4$  matrix inverse calculation with a simpler  $2 \times 2$  matrix.

Transition matrix A

$$A = \begin{bmatrix} 1 & 0 \\ 1 - \frac{d \cdot h_{t-1}}{h \cdot f} & 1 \\ 0 & 1 \\ 0 & 1 - \frac{d \cdot w_{t-1}}{w \cdot f} \end{bmatrix} \dots\dots\dots (15)$$

Measurement matrix H:

$$H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \dots\dots\dots(16)$$

The spatial constraints of the road sign size and location between two successive frames constitute a dynamic equation which functions as a time update step in the Kalman filter. The goal is to combine tracking with other rules from the color and shape criteria produce a working set of algorithms for sign inventory. Fig.4 shows the flow chart of the Kalman filter based tracking in detail.

**Recognition**

As the candidate region is tracked when the vehicle moves toward the sign and size of the sign is increased, it will come to a stage that the sign in the picture is obvious and the disturbance from the background is insignificant to influence the outcome. The candidate region is matched by template before it is out of view in the camera, that is, in the last frame in the tracking process. Five series of templates are used in pixel: 120×120, 100×100, 80×80, 60×60, 40×40. For each size template, 3 levels of contrasts are used. Figure 5 shows the template for stop sign. Once the road sign is recognized in the template matching, the tracking is marked as successful.

**GPS/GYRO positioning**

The last step is mapping the detected road sign using GPS/GYRO information. Depending on the GPS receiver, the positioning accuracy varies. The data from GPS receiver is adjusted by local GYRO information. The integration of the GPS receiver and GYRO sensor provide more accurate location information for the detected road sign than just using the GPS data alone.

**EXPERIMENT**

Since the mid-1990’s, research team at the University of Arkansas has engaged in the development of a full digital vehicle for highway data collection, this Digital Highway Data Vehicle (DHDV) has evolved into a new platform shown in Fig. 6. The DHDV is multi-functional and includes a sub-system for pavement surface imaging for condition survey at 1-mm resolution, longitudinal roughness consisting of laser sensors and accelerometers, laser based rutting measurement device with over 1,000 transverse points, Right-of-Way (ROW) images, GPS receiver, DMI, and Gyro sensor. The software system used in the on-board computers of the DHDV employs real-time relational database engine, inter-computer communication techniques, multi-computer and multi-CPU based parallel computing, real-time control of digital sensors, and the generation of multimedia databases.

For right-of-way imaging, there are two digital color frame cameras mounted on top of the DHDV. Each camera is at the resolution of 1300 by 1024. The imaging system can record and archive one frame color image from the camera at user-determined interval up to one frame per 10 feet. In this experiment, one camera is used for the research.

**Statistical Test and Calibration**

The Q and R term in the Kalman filter model have to be determined in advance. Statistical study of the ROW images is conducted to determine this two terms. The error of the dynamic model Q will come from the instrument (the vehicle velocity and direction, DMI and other instrument). Q is obtained by taking photos for the same road sign from the same distance 20 times. The error covariance of the location state vector is first calculated from the 20 images.

$$e = \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} \dots\dots\dots(17)$$

Then substitute to equation (18) to obtain the Q term.

$$Q = e^T \cdot e = \begin{bmatrix} e_1 & e_2 \end{bmatrix} \cdot \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} = \begin{bmatrix} e_1e_1 & e_2e_1 \\ e_1e_2 & e_2e_2 \end{bmatrix} \dots\dots\dots(18)$$

The Q term for the size state vector is obtained in the same way. The statistical study also shows that the error covariance for the size state vector is much smaller than the error covariance of the location state vector. This is another reason why the state vector  $x = (x_t, y_t, h_t, w_t)^T$  is split into two. Measurement error covariance term R is determined from the success probability in image processing which is based on correct/false detection ratio. The error of the measurement (image processing) comes from the accuracy of the detection algorithms. In this test, it is set to be very small since the measurement (image processing) in the predicted limited region is relatively accurate.

Another important thing is to calibrate the effect focal length. The focus of the camera lens is 11-mm. The effective focal length is calibrated by using the known distance L and known road sign size h in the 20 pictures. H is the physical height of the stop sign. The effective focal length of the camera is the average value of the calibration based on the 20 images.

$$f = \frac{hL}{H} \dots\dots\dots(19)$$

**Experiment Result**

The determined Q, R and *f* are input parameters in the system. In the experiment, the size of the image is 1300 x 1024, the DMI distance, GPS latitude, longitude, altitude, Gyro information are given for each image. The interval distance between two successive images is obtained from DMI measurement. Figure 7 shows the interface of the road sign detection software. The GPS information, current state vector and tracking status are displayed instantly while the vehicle is in motion. The ROW images are processed in real time.

Five road tests are conducted. The results in Table 1 show the accuracy based on the Kalman filter tracking algorithm. Table 1 also lists the false and success detection of the road sign in the five road tests. The majority of the road sign can be detected and tracked accurately. The successful detection rate is about 95%.

Figure 8 shows how Kalman filter tracking works while the vehicle is in motion. This is a typical ROW environment of a local street which has some complicated background, such as a sign in the intersecting street, and greenery. The candidate region starts to be detected at size 12 x 12 pixels. Once the Kalman tracking is activated, the candidate region is highlighted with boundary box. Figure 8 shows the last frame containing the entire candidate region before it is out of view in the camera. Subsequently, the candidate region is normalized and matched with one of the five templates. The result of the matching returns a fail or success detection and be marked as a successful tracking if so. The GPS location data is recorded with a successful tracked target as well.

Figure 9 demonstrates that the Kalman filter tracking algorithm successively captures multiple road signs. This illustrates that the tracking technique is effective in automated inventory of road signs, overcoming difficulties in using traditional imaging techniques for multiple targets. Detection of the signs would create errors and require substantial more computing resources with traditional imaging methods. The 15 frames are picked out from the images of about 100-meter distance. There are 3 pedestrian crossing warning signs and one speed limit sign. Frames 1 to 3 show that the first pedestrian sign is tracked until it is out of view. Frames 7-13 show the existence of the second and the third signs at the same time while they are tracked separately. The two signs belong to two different tracking processes. This methodology effectively improves the accuracy of sign identification. Frames 14 and 15 capture the last pedestrian sign.

**CONCLUSION**

There have been limited published literature on automated inventory of roadway signs, despite the fact that there were several attempts in recent years in the ITS arena to detect sign for the purpose of automated driving and navigation. A methodology for automated inventory of road sign by image analysis and Kalman filter tracking with ROW images has been tested successfully. The algorithms have four main parts, the detection, tracking, recognition and GPS mapping. The detection is based on color and shape information. The Kalman filter tracking algorithm makes the detection more robust and efficiency. The recognition is accomplished by template matching. The GPS position system provides positioning data for

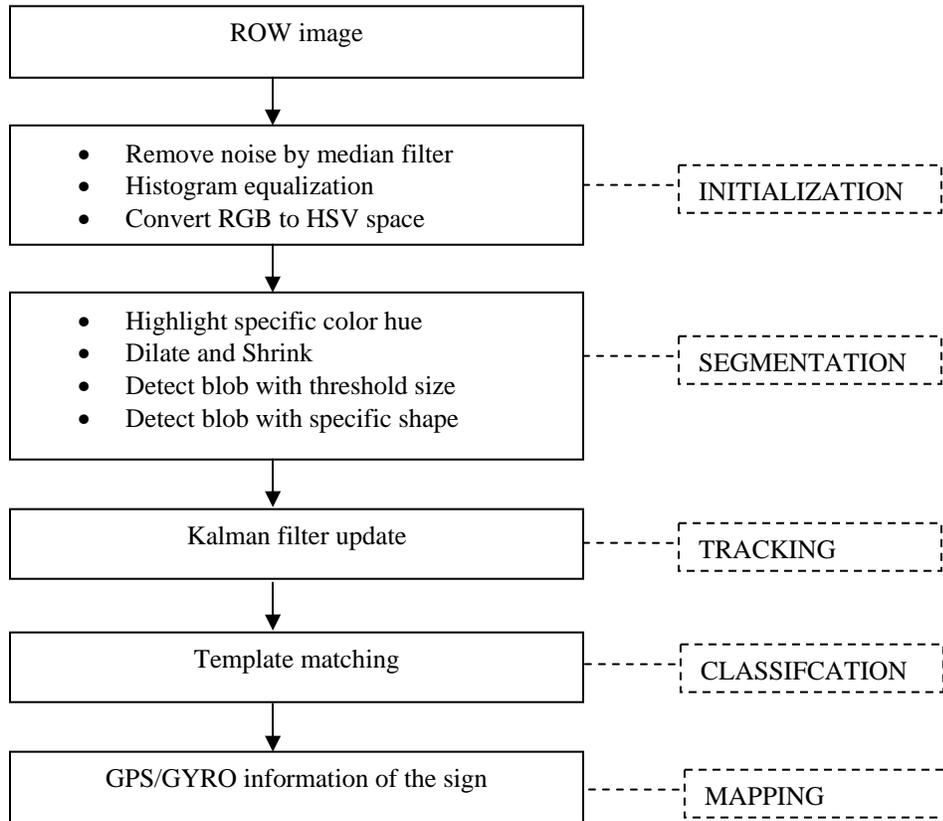
road sign. It is also demonstrated that the techniques can successfully track and detect multiple signs in the same sequence of images. Based on our initial experimentation with the algorithms and models presented in the paper, it is hopeful that comprehensive and fully automated inventory of roadway signs can be realized.

#### **ACKNOWLEDGEMENT**

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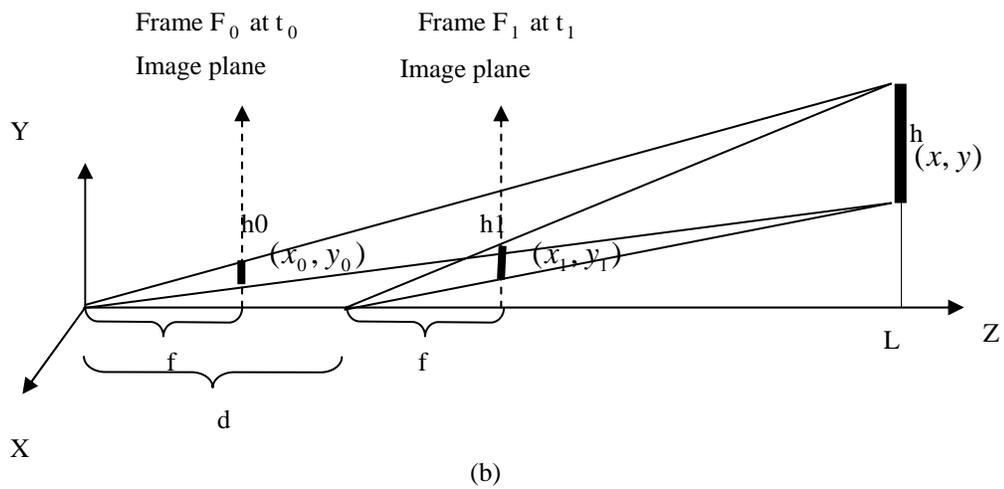
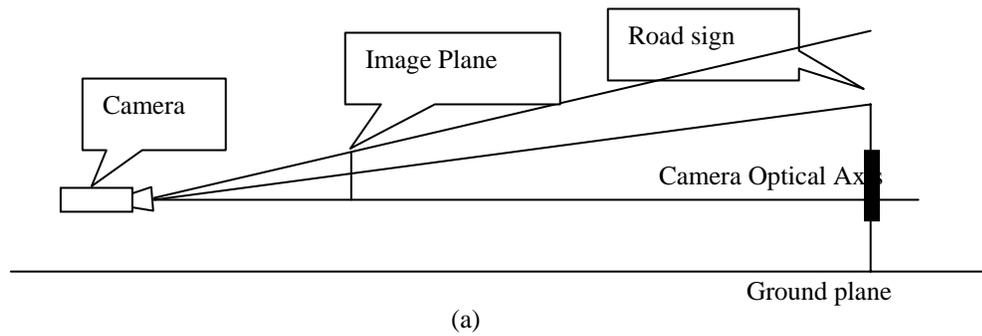
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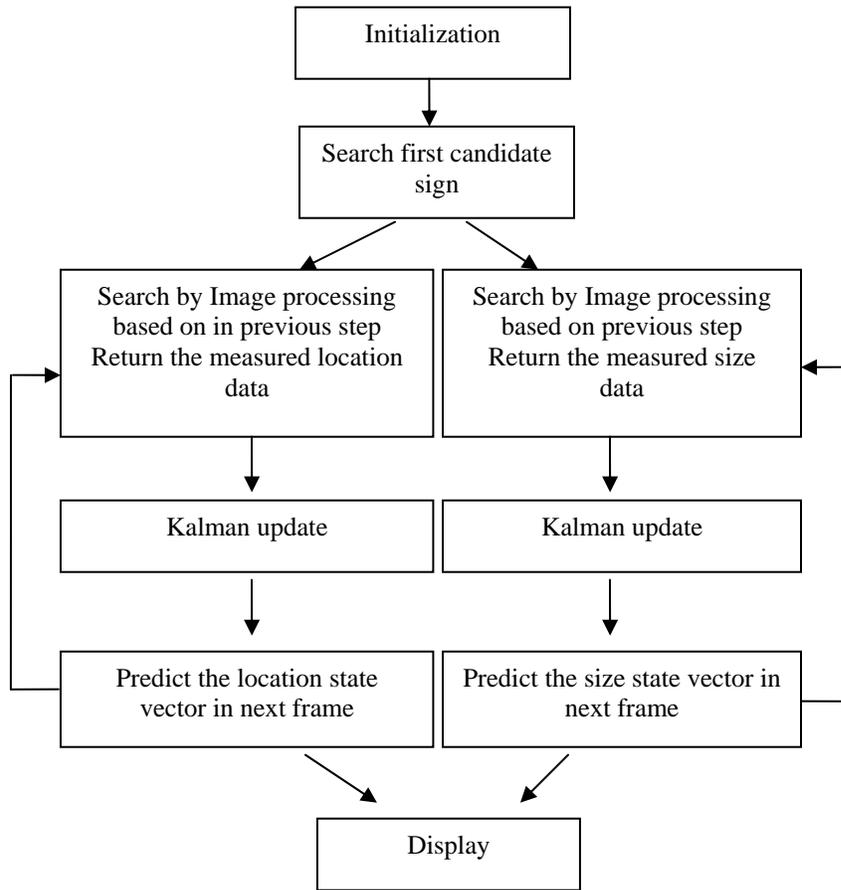
**FIGURE 1** Flow chart of the algorithm.



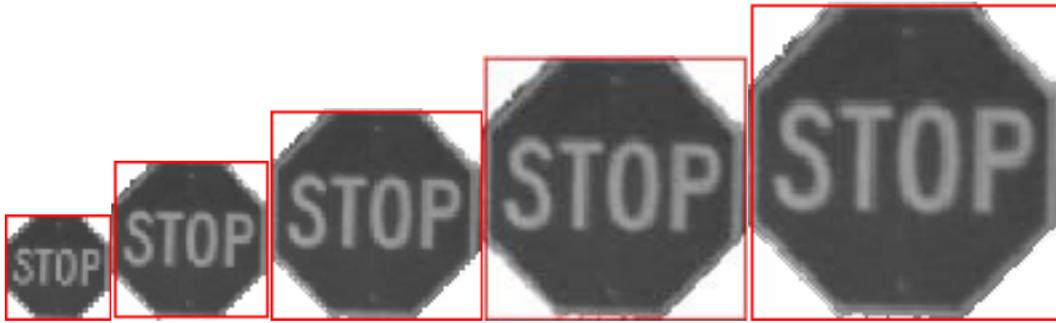
**FIGURE 2** Road sign figures Vs processed images.



**FIGURE 3 Spatial constraints in two successive frames.**



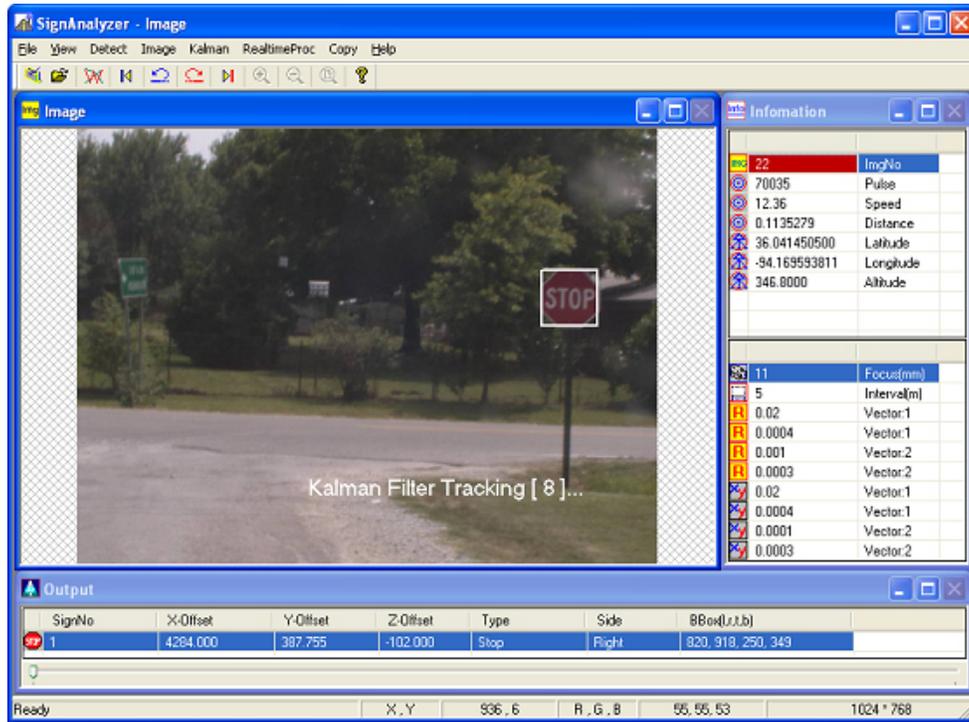
**FIGURE 4** Flow chart of the Kalman filter tracking.



**FIGURE 5** Different sizes of the stop sign templates.



**FIGURE 6** the DHDV(Digital Highway Data Vehicle).



**FIGURE 7** Interface of the road sign detection software.



**FIGURE 8** Detection and tracking of a single road sign.



**FIGURE 9** Detection and tracking of multiple signs.

**TABLE 1 Performance of the Stop Sign Detection**

Test	#Frames	# Stop Signs	#Correct Tracking	#False tracking
1	8324	35	33	1
2	12549	47	44	0
3	6123	23	22	0
4	2678	15	12	1
5	9082	38	36	0