# Efficient Stop & Warning Sign and Pedestrian Detection

Castleberry, Cherry, and Firth

December 6, 2012

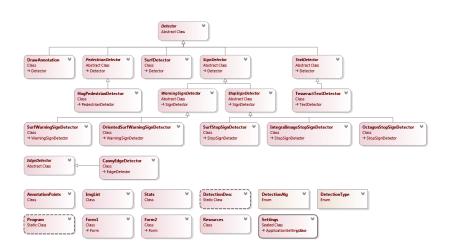


#### Overview

- We implemented the following:
  - Stop-sign detector, using the notion of integral images from SURF
  - Warning sign detector, using perspective transformation on a model image, then SURF

#### Wrappers

- We created a wrapper to the pedestrian detector to gain familiarity with the EmguCV library.
- We also created a wrapper to the built-in EmguCV SURF detector to use as a basis of comparison for our own methods.



Introduction and Overview Stop Signs Warning Signs Results and Conclusion





- We developed a method for detecting stop signs based upon the use of integral images which we encountered in the SURF algorithm.
- To summarize the method, we use integral images from both the left-hand side (top left) and the right-hand side (bottom right) on only the R channel. Then we consider only the LHS and RHS integral images along the diagonal of the image. We difference these, then fit a Gaussian curve to the resulting vector. We threshold the curve at the points of inflection to generate a bounding box for the sign.

Introduction and Overview Stop Signs Warning Signs Results and Conclusion



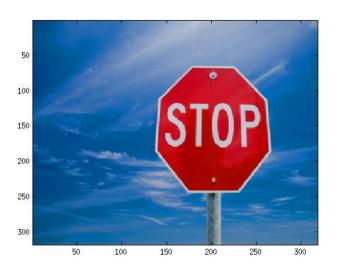
- To begin our method, we scale the  $N \times M$  image to  $N \times N$  for N < M,  $M \times M$  for M < N. We require a square matrix to extract a particular vector.
- Recall that the formula for computing the integral image  $\mathcal{I}_{-}$  at a pixel (x,y) with intensity value I(x,y) is:

$$\mathcal{I}_{-}(x,y) = \sum_{i=0}^{n_x} \sum_{j=0}^{n_y} I(x,y)$$
 (1)

 We compute the integral image at a pixel using the following formula:

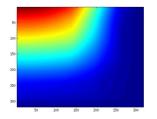
$$\mathcal{I}_{x,y} = \mathcal{I}_{x-1,y} + \mathcal{I}_{x,y-1} - \mathcal{I}_{x-1,y-1}$$
 (2)

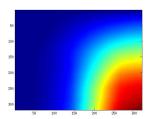




• Likewise, we compute an RHS integral image  $\mathcal{I}_+$  at a pixel (x,y) with intensity value I(x,y) as:

$$\mathcal{I}_{+}(x,y) = \sum_{i=N}^{n_{x}} \sum_{j=N}^{n_{y}} I(x,y)$$
 (3)



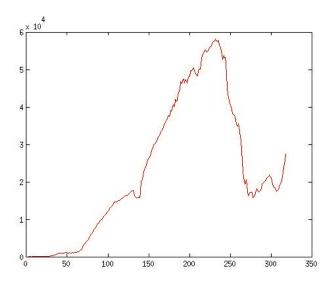


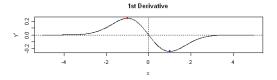
- After obtaining the integral image, we copy its diagonal into a vector u.
- We then apply a finite-difference method to the elements in u
  and store it in v, as follows:

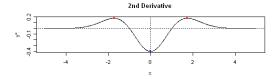
$$v_n = u_n - u_{n-1} \tag{4}$$

The vector v gives the LHS crosshair of the R-channel. For images which have stop signs, v has a Gauss distribution.

- We apply this finite-difference method for both vectors u<sub>-</sub> and u<sub>+</sub> to obtain v<sub>-</sub> and v<sub>+</sub>.
- Then, we add  $v_-$  and  $v_+$  to obtain a vector m.
- Finally, we compute the standard deviation  $\sigma$  of the vector m and its centroid c, then apply a Gaussian fit to the data in m. We call the Gaussian fit G.
- We then apply finite-differencing to the Gaussian fit G to obtain G', then find the indices at min(G') and max(G').
- These indices form the bounding box for the image.







# Warning Signs

- For our warning sign detection, we experimented with SURF in combination with perspective transformations on out-of-plane-rotated signs.
- In particular, we assume that we know the perspective information of an out-of-plane-rotated sign. We apply a perspective transform to a model sign, then apply SURF to the two images, then match.

Introduction and Overview Stop Signs Warning Signs Results and Conclusion



# Warning Signs

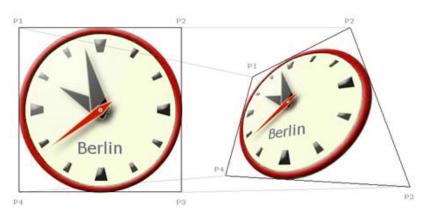
- We first hand-annotated N images using a MATLAB code.
- From this, we extracted a set of 4N points which give the vertices of the warning sign. We then applied getPerspectiveTransform() on the points, which returns a perspective transform matrix M.
- We apply this perspective transform matrix to the model with the function warpPerspective().
- We then run SURF on the two images, then compare their feature descriptors to obtain a match within a threshold of  $t_{\epsilon}$ .

# Perspective Transform

• If  $a_{x,y,z}$  is the point to be projected,  $c_{x,y,z}$  is the camera,  $\theta_{x,y,z}$  is the camera orientation and  $e_{x,y,z}$  is the position of the viewer relative to the display surface then  $b_{x,y}$ , the 2D projection of a, is given by:

$$\begin{bmatrix} d_X \\ d_y \\ d_z \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\theta_X) & -\sin(\theta_X) \\ 0 & \sin(\theta_X) & \cos(\theta_X) \end{bmatrix} \begin{bmatrix} \cos(\theta_y) & 0 & \sin(\theta_y) \\ 0 & 1 & 0 \\ -\sin(\theta_y) & 0 & \cos(\theta_y) \end{bmatrix} \begin{bmatrix} \cos(\theta_z) & -\sin(\theta_z) & 0 \\ \sin(\theta_z) & \cos(\theta_z) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} \begin{bmatrix} a_X \\ a_y \\ a_z \end{bmatrix} - \begin{bmatrix} c_X \\ c_y \\ c_z \end{bmatrix}). \tag{5}$$

A visual example follows.



Source Surface

**Destination Surface** 

#### Results

- We considered there to be a match if at least 50% of the sign fell within the area of the bounding box.
- The following table summarizes our results:

Surf Stop Sign Detector Integral Images Stop Sign Detector Surf Warning Sign Detector Oriented Surf Warning Sign Detector

As is evident in the above, our accuracy for . . . was an abysmal N%.

#### Conclusion

- Bearing in mind that the accuracy for our integral image detector was much less than the accuracy for the built-in SURF algorithm, we conclude that in the development of computer vision algorithms, one should:
  - Not over-utilize heuristics, and
  - Oevelop the algorithm starting from optimized versions of existing algorithms.