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Intelligent Auto Horn System Using Artificial Intelligence

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Abstract - *The increasing levels of noise pollution pose a major threat to human health and the environment. Blaring unnecessarily close to neighbourhoods, schools sign and clinics is for the most part impacted and unequivocally wanted. We propose a brand-new honking mechanism that would substantially reduce horn blowing noise. The current mechanism does not compromise the safety of individuals inside and around the vehicle. The vehicle's fixed horn system is used in our proposed mechanism. Using artificial intelligence, our horn system automatically adjusts the horn sound to the distance between people, the width of the road, and the size of the object. As a result, artificial intelligence will control the horn's sound.*

Key Words - Intelligent Vehicle Horn System

1. INTRODUCTION

Horn system is fitted with numerous sensors; cameras and manual horn switch to generate massive amounts of environmental data. All of these form the Digital Sensorium, through which the independent vehicle can see and feel the objects, road infrastructure, other vehicles and every other object on/near the road, just like a human driver would pay attention to the road while driving.

1.1 AI Data Collection & Communication Systems

This data is then processed with inbuilt chip and data communication systems. These are used to Only push the on switch, and it will automatically return to its original position.

- The horn switch will operate for a period of five seconds.
- We can't press the switch for more than a second at a time.
- We can't change the horn system because doing so would damage the entire device.
- The device won't function if people aren't on the road or if animals cross or sleep.
- Finally, the horn will sound both horizontally and vertically depending on the width of the road.
- Those who are walking alongside the vehicle, on the footpath, or inside the building cannot hear the horn.

1.2 Mathematics:

$D(x,y,\sigma)=(G(x,y,k\sigma)\ G(x,y,\sigma)) * I(x,y)$

$= L(x,y,k\sigma)\ L(x,y,\sigma)$

Where * is the convolution operator,

$G(x,y,\sigma)$ is a variable scale Gaussian,

$I(x,y)$ is the input image $D(x,y,\sigma)$

is Difference of Gaussians with scale k times. [1]

2. HEADING

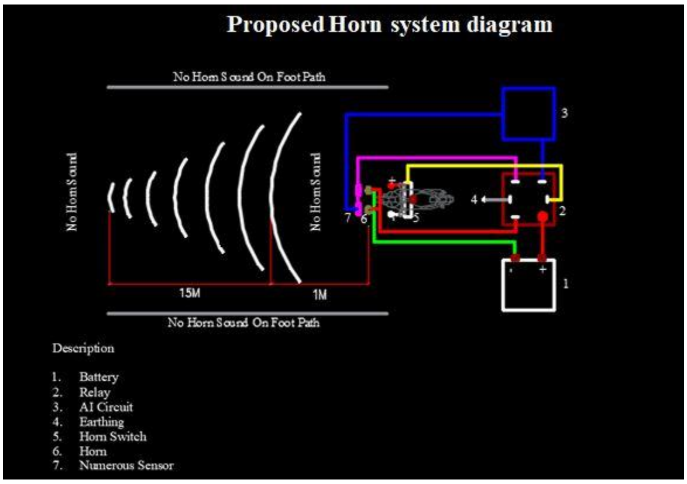

Fig -1: Proposed Horn System Diagram

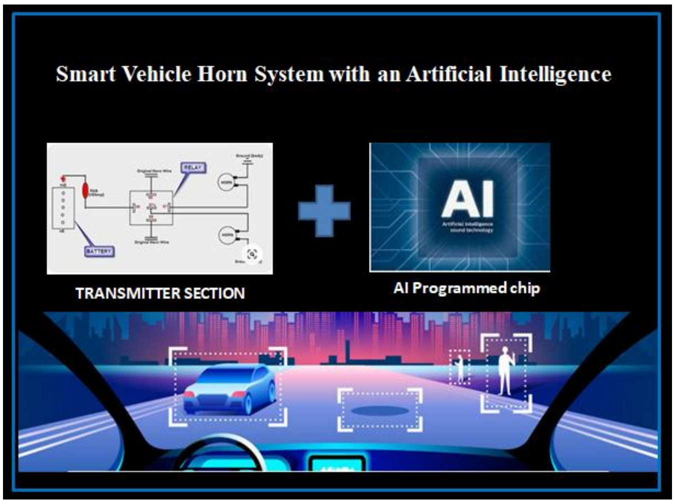

Fig -2: The Data connection between objects

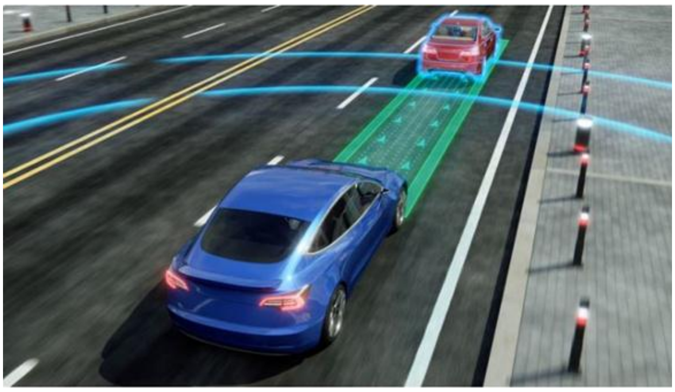

Fig -3: Horn Sound Blow out side 1.0 mtr Radius

3. SIFT ALGORITHM

Scale Invariant Feature Transform (SIFT) features are features extracted from images to help in reliable matching between different views of the same or different object. [6] The extracted features are invariant to scale and orientation, and are highly distinctive of the image. They are extracted in four steps. The first step distance sensor the locations of potential interest points in the image by detecting the maxima and minima of a set of Difference of Gaussian (DoG) filters applied at different scales all over the image. Then, these locations are refined by discarding points of low contrast. An orientation is then assigned to each key point based on local image features. Finally, a local feature descriptor is computed at each key point. This descriptor is based on the local image gradient, transformed according to the distance of the key point to provide orientation invariance. Every feature is a vector of dimension 128 distinctively identifying the neighborhood around the key point. The following steps are involved in SIFT algorithm:

3.1 Scale-space Extreme Detection: The first stage of computation searches over all scales and image locations. It is implemented efficiently by using a difference-of-Gaussian function to identify potential interest points that are invariant to scale and direction.

3.2 Key point localization: At each object location, a detailed model is fit to determine location and scale. Key points are selected based on measures of their stability.

3.3 Orientation assignment: One or more orientation is assigned to each key point to achieve invariance to image distance. A neighbourhood is taken around the key point location depending on the scale, and the gradient magnitude and direction is calculated in that region.

3.4 Key point descriptor: The local image gradients are measured at the selected scale in the region around each key point. These are transformed into a representation that allows for significant levels of local shape distortion and change in illumination. The first stage used difference-of-Gaussian (DOG) function to identify potential interest points, which were invariant to scale and orientation. DOG was used instead of Gaussian to improve the computation speed.

$D(x,y,\sigma)=(G(x,y,k\sigma)\ G(x,y,\sigma)) * I(x,y)$

$= L(x,y,k\sigma)\ L(x,y,\sigma)$

Where $*$ is the convolution operator,

$G(x,y,\sigma)$ is a variable scale Gaussian,

$I(x,y)$ is the input image $D(x,y,\sigma)$ is Difference of Gaussians with scale k times.

For any object in an image, interesting points on the object can be extracted to provide a "feature description" of the object. This description, extracted from a training image, can then be used to identify the object when attempting to locate the object in a test image containing many other objects. To perform reliable recognition, it is important that the features extracted [11] from the training image be detectable even under changes in image scale, noise and illumination. Such points usually lie on high-contrast regions of the image, such as object edges and distance.

SIFT key points: [5] of objects are first extracted from a set of reference images and stored in a database. An object is recognized in a new image by individually comparing each feature from the new image to this database and finding person/object matching features based on Euclidean distance of their feature vectors. From the full set of matches, subsets of key points that agree on the object and its location, scale, and orientation in the new image are identified to filter out good matches. The determination of consistent clusters is performed rapidly by using an efficient . Each cluster of 3 or more features that agree on an object and its pose is then subject to further detailed model verification and subsequently outliers are discarded. Finally the probability that a particular set of features indicates the presence of an object is computed, given the accuracy of fit and number of probable false matches. Object matches that pass all these tests can be identified as correct with high confidence.

3.5 Key point Matching: Key points between two images are matched by identifying their nearest neighbours. But in some cases, the second closest-match may be very near to the first. It may happen due to noise or some other reasons.

Another important characteristic of these features is that the relative positions between them in the original scene shouldn't change from one image to another. For example, if only the four corners of a road were used as features, they would work regardless of the object position; but if points in the frame were also used, the recognition would fail if the road is long or closed. Similarly, features located in articulated or flexible objects would typically not work if any change in their internal geometry happens between two images in the set being processed. However, in practice SIFT detects and uses a much larger number of features from the images, which reduces the contribution of the errors caused by these local variations in the average error of all feature matching errors.

SIFT can robustly identify objects even among clutter and under partial occlusion, because the SIFT feature descriptor is invariant to uniform scaling, distance, and partially invariant to affine distortion and illumination changes. This section summarizes Lowe's object recognition method and mentions a few competing techniques available for object recognition under clutter and partial occlusion.

In the key point localization step, they are rejected the low contrast points and eliminated the edge response. Hessian matrix was used to compute the principal curvatures and eliminate the key points that have a ratio between the principal curvatures greater than the ratio. An orientation histogram was formed from the gradient orientations of sample points within a region around the key point in order to get an orientation assignment. According to experiments, the best results were achieved with a 4x4 array of histograms with 8 orientation bins in each. So the descriptor of SIFT that was used is 4x4x8= 128 dimensions.

4. PCA-SIFT

PCA-SIFT: Principal Component Analysis (PCA) is a standard technique for dimensionality reduction and has been applied to a broad class of computer vision problems, including feature selection. PCA-SIFT can be summarized in the following steps :

- Pre-compute an Eigen space to express the gradient images of local patches
- Given a patch, compute its local image gradient
- Project the gradient image vector using the Eigen space to derive a compact feature vector.

The input vector is created by concatenating the horizontal and vertical gradient maps for the 41x41 patch centered at the key point. Thus, the input vector has 2x39x39=3042 elements. Then normalize this vector to unit magnitude to minimize the impact of variations in illumination. Projecting the gradient patch onto the low-dimensional space appears to retain the identity related variation while discarding the distortions induced by other effects. Eigen space can be built by running the first three stages of the SIFT algorithm on a diverse collection of images and collected 21,000 patches. Each was processed as described above to create a 3042-element vector, and PCA was applied to the covariance matrix of these vectors. The matrix consisting of the top n eigenvectors was stored on disk and used as the projection matrix for PCA-SIFT. The images used in building the Eigen space were discarded and not used in any of the matching experiments [11].

5. SURF

A basic second order Hessian matrix approximation is used for feature point detection. The approximation with box filters is pushed to take place of second-order Gaussian filter. And a very low computational cost is obtained by using integral images. The Hessian-matrix approximation lends itself to the use of integral images, which is a very useful technique. Hence, computation time is reduced drastically [10]. In the construction of scale image pyramid in SURF algorithm, the scale space is divided into octaves, and there are 4 scale levels in each octave. Each octave represents a series of filter response maps obtained by convolving the same input image with a filter of increasing size. And the minimum scale difference between subsequent scales depends on the length of the positive or negative lobes of the partial second order derivative in the direction of derivation.

6. OTSU'S ALGORITHM IN IMAGE SEGMENTATION

Threshold is one of the widely methods used for image segmentation. It is useful in discriminating foreground from the background. By selecting an adequate threshold value T, the gray level image can be converted to binary image.

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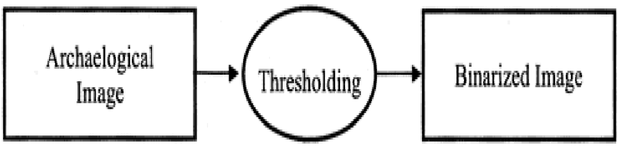

Fig. 4. The process of thresholding along with its inputs And outputs

The binary image should contain all of the essential

Information about the position and shape of the objects of interest (foreground).

If g(x, y) is a threshold version of f(x, y) at some global

Thres hold T it can be defined as [1],

$g(x, y) = 1$ if $f(x, y) \geq T$=0 otherwise

Thres holding operation is defined as:

$T = M [x, y, p(x, y), f (x, y)]$

6.1 Global thresholding

When T depends only on f (x, y), only on gray-level values and the value of T solely relates to the character of pixels, this thresholding technique is called global thresholding.

6.2 Local thresholding

If threshold T depends on f(x, y) and p(x, y), this thresholding is called local thresholding. This method divides an original image into several sub regions [12], and chooses various thresholds T for each sub region reasonably [13].

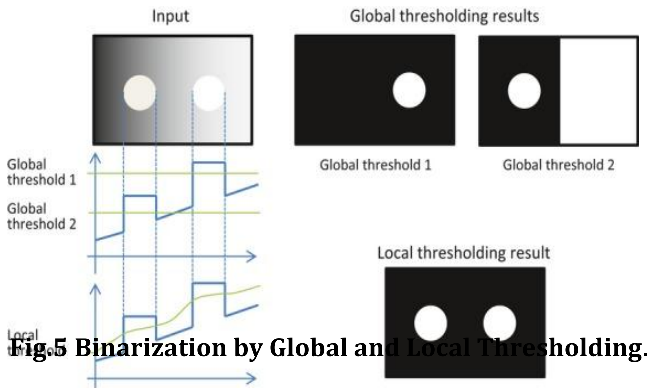

Fig.5 Binarization by Global and Local Thresholding.

Read the two images.

```
I1 = imread('cameraman.tif');
```

Find the SURF features.

```
Points=detectSURFFeatures(I);
[features,valid_points]=extractFeatures(I,points);
```

Visualise

10 strongest SURF features including scale and orientation which was determined during the descriptor extraction process

```
Figure,imshow(I);hold on;
lot(valid_points.selectStrongest(10),'showOrientation',true);
```

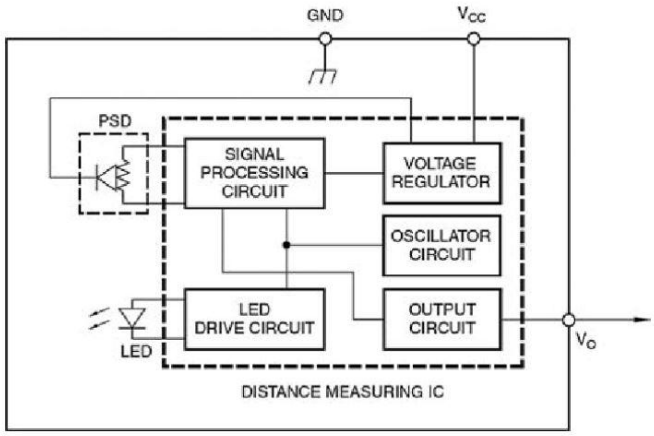

Fig -6: Block diagram showing the distance measuring from the range sensor.

Fig -7: Vehicle Image showing the distance measuring from the range sensor.

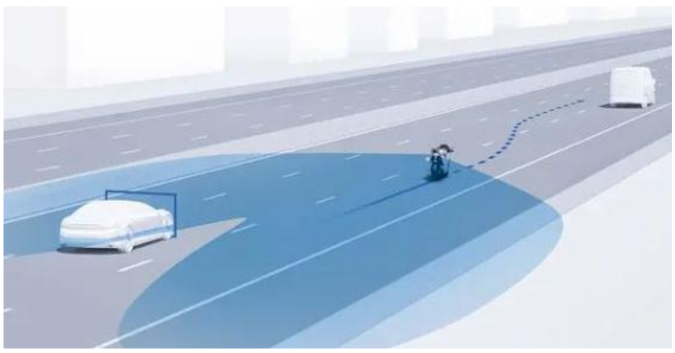

Fig -8: Single-sensor-based chord offset synchronizing model

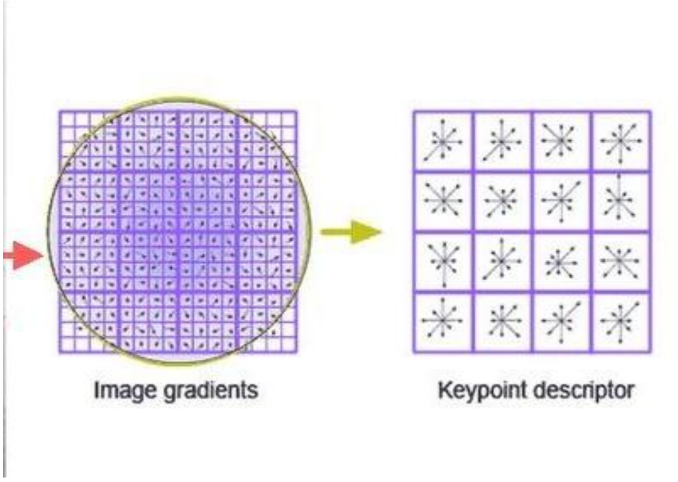

Fig -9: Feature Point Detection using SIFT

7. HORN THEORY

The horn system includes the following terminology:

Impedance: Quantity impeding or reducing flow of energy. Can be electrical, mechanical, or acoustical.

Acoustical Impedance: The ratio of sound pressure to volume velocity of air. In a horn, the acoustical impedance will increase when the cross-section of the horn decreases, as a decrease in cross section will limit the flow of air at a certain pressure.

Volume Velocity: Flow of air through a surface in m3/s, equals particle velocity times area.

Throat: The small end of the horn, where the driver is attached. Mouth: The far end of the horn, which radiates into the air.

Driver: Loudspeaker unit used for driving the horn.

c: The speed of sound, 344m/s at 20° C.

ρ_0: Density of air, 1.205 kg/m^3.
f: Frequency, Hz.
ω: Angular frequency, radians/s, $\omega = 2\pi f$.
k: Wave number or spatial frequency, radians/m, $k = \frac{\omega}{c} = \frac{2\pi f}{c}$.

S: Area.
p: Pressure.
Z_A: Acoustical impedance.
j: Imaginary operator, $j = \sqrt{-1}$.

7.1 Volume and speed correction:

The hourly flow of each vehicle category (Veh/hr) and the average speed of each category (km/hr) are used for calculation of Leq value. Therefore this model incorporated the volume speed correction that is applied for final Leq value. The correction is given as:

Avs = 10 Log (DO V/S) -25

Where,

V = Volume for the category (Veh/hr)
S = Speed (km/hr)
DO = Reference distance (m/s)

7.2 Distance correction:

When calculating distance adjustment the type of intervening ground cover between the highway and reception point is also considered.

AD = 10 Log 10 (DO/ D) 1 + α]

Where,

DO = Reference distance given as 10 meters
D = Distance of measurement from center of each Lane

α = Ground cover coefficient

8. EXPERIMENTAL RESULT

Scale Invariant Feature Transform is used to extract features from the ID. The implementation is done using MATLAB. Feature extraction enables you to derive a set of feature vectors, also called descriptors, from a set of detected features. Computer Vision System Toolbox offers capabilities for feature detection and extraction.

SURF is used to detect blobs and regions. The SURF local feature detector function is used to find the corresponding points between different images that are near/far and scaled with respect to each other.

In accordance with another preferred embodiment of the invention, the positioning system further comprises supplementary sensors, such as Tacho/ABS sensors or Gyro sensors.

In accordance with another preferred embodiment of the invention, the alarm is an audio alarm and/or an optical alarm.

According to the invention, at a location that honking is forbidden or restricted, the horn of a vehicle is automatically deactivated or the sound level is lowered, and/or the driver receives an alarm that the horn should not be used. Thus, horn noise will be effectively controlled in specified areas. In addition, at a location that honking must be performed, the horn of a vehicle is automatically operated to generate sound, and/or the driver receives an alarm that the horn should be operated to generate sound. Thus, traffic safety can be improved.

The present invention in a second aspect provides an automatic vehicle horn control method comprising: a) acquiring information about horn operating regulation related with current or concerned location and driving direction of the vehicle; b) if at current or concerned location and in current or concerned driving direction it is not allowed to operate the horn to produce sound or the sound level is not allowed to be higher than a certain level, then a honking forbidden or restriction mode is initiated in which the horn is deactivated or the sound of the horn is controlled to be lower than a certain level, and/or an alarm indicating the honking forbidden or restriction requirement is generated,

CONCLUSIONS

Using a distance parameter between a person and other objects, this device can monitor and control the sound of the vehicle horn.

We can send these data to a faraway location around the world to create a sound graph report.

When it is manufactured in large quantities, this device will be relatively inexpensive.

If the sound of the vehicle horn goes away within five years, this will have a good future and be a complete success.

ACKNOWLEDGEMENT

Despite the fact that the Earth has provided us with all of the necessary resources for our existence. The numerous levels and domains of life, as well as the biosphere, lithosphere, atmosphere, and hydrosphere, are in perfect harmony. As a result of this coordination and synchronization, we might be able to live a long and healthy life here on Earth.

Numerous factors, including increasing sound, vibration, heat, and climate change, are depleting Earth's resources. The depletion of our Earth's resources is evident in all of these signs, and it is time to save our planet: The ice is going away; woodlands are consuming; The fields are dry and empty; oceans are unsteady; The water is imperfect and vibrates at a higher frequency. We can help ourselves by reducing the earth's vibration.

Fig -10: Only One Earth

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