

A Survey Based on Image Defogging

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ABSTRACT: Defogging in visibility is often introduced to images captured in poor weather conditions, such as haze, rain, fog, pollutants particles. To remove haze, and other pollutants from the image many algorithm are used, here mainly used is Gaussian -based dark channel. The Gaussian -based dark channel method improves is used to improve the light source in the image. All the images taken in a poor weather has a flickering effect, to remove flickering effect a flicker free module is formulated. So overall the image is enhanced to get a quality image.

KEYWORDS: Defogging, haze, rain, pollution, dark channel, enhancement, Confidence-encoded SVM, Context modeling, Contrast Restoration, polarization, interactive, image restoration.

I. INTRODUCTION

Visual application is important aspect for any detection. The image detection are used in many fields, one such as object tracking needs a clear image to track the object. However, it is common that in a poor weather conditions, like haze, rain, defog, dehaze the image quality degrades. The image defogging [10] is occurred due to frequently exposure to strong light, rain, snow, fog. The Confidence-encoded SVM [8] is used to detect a particular image in a video, here they are transferring generic pedestrian detector to a scene-specific detector. This involves four steps, all these four steps considerations are formulated under a single objective function called confidence-encoded svm. Context modeling [7] framework is used and they formulate polar geometric context, in order to quantify context they use new margin context. Tools used here are PASCAL VOC2005 and VOC2007 data sets, they detect two things luggage and vehicle with the help of i-LIDS data set and outdoor surveillance footage. Chromatic Atmospheric Scattering [1] is a study done on different climatic conditions, here the three dimensional structure is proposed, the chromatic model is derived in several geometric constraints on scene color changes caused by varying atmospheric conditions. The traditional image processing techniques where not sufficient to remove weather effects from images, thus they introduced a physics-based model that describes the appearances of scenes in uniform bad weather conditions proposed a fast algorithm [3]. Gaussian -based method computed fusion weighting scheme and the atmospheric light it improves the light source. Contrast Restoration [5] has three tools to enhance a moving vehicle a restoration method based on Koschmieder's law, a scene depth modeling and an image quality attribute used to evaluate the quality of the restoration. Single image haze removal [6] uses the Gaussian -based method because the original image has a very low intensities. Polarization [4] solves the spatially-varying reduction of contrast by stray radiance (airlight). Interactive algorithms [2] are used to remove weather effects from, and add weather effects to, a single image. Physical model[9] is used in a computer vision in order to have a haze free image in different climatic conditions earlier they used polarization now to have a better enhancement in the image a physical model is used. Thus image processing is enhanced by all this methods to get a quantitative and quality image.

II. RELATED WORK

Shree K. Nayar and Srinivasa G. Narasimhan in the year 1999 explains all about the bad weather and they have studied different weather conditions and identifying effects caused by the poor weather and trying to make the effects as advantages and the images where transformed into the three dimensional structure.

Srinivasa G. Narasimhan and Shree K. Nayar in the year 2003 explains the de-weathering and physics based model developed three interactive algorithms to remove weather effects from and add weather effects to a single image.

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Srinivasa G. Narasimhan and Shree K. Nayar in the year 2003 explained about the right amount of light required to the camera and they have proposed technical method to have a good image. In technical method they used fast algorithm to overcome the pollutants in the images.

SaritShwartz, EinavNamer and Yoav Y. Schechner in the year 2006 explains about the major problem spatially-varying reduction. To get a haze free image the polarization-filtered image are used in the outdoor image to get a quality image. Nicolas Hautière, Jean-Philippe TarelDidierAubert in the year 2007 they explained about the contrast of images grabbed by cameras to the vehicle in the low light and bad weather, they used different algorithms to increase complexity.

Kaiming He, Jian Sun, Xiaou Tang in the year 2010 tell us about prior-dark channel, to remove all the pollutants such as haze, rain, rain, snow from a single input image. They use a high-quality haze free image to remove all the pollutants.

Wei-Shi Zheng, Member, Shaogang Gong, and Tao Xiang in the year 2012, proposed a novel context modeling and used to formulate polar geometric context. The tools used here are PASCAL, VOC2005 and VOC2007. They are used to detect the objects with the help of surveillance. The PASCAL VOC2005 dataset includes car, motorbike, people and bicycle. In PASCAL VOC2007 dataset includes aeroplane, bus, cat, cow, horse and train.

Xiao gang Wang, Meng Wang, and Wei Li in the year 2014 wrote a paper Scene-Specific Pedestrian Detection for static video surveillance where it detects an object in a video , they transfer generic pedestrian detector to a scene-specific detector, it involves four steps and these four steps considerations are formulated under a single objective function called confidence-encoded SVM.

Qingsong Zhu, Jiaming Mai, Ling Shao in the year 2015 address about the color attenuation prior in this paper to remove the haze from a single input image , they use depth map and restore the radiance through the atmospheric light .

Jing-Ming, Guo, Jin-yuSyue, VincentRadzicki, HuaLee, Fellow in the year 2017 wrote a paper based on defogging , it deals with different algorithm Li, Tarel, Hazy, He, Meng, Lai, Zhu, Tang , Kim , Kolor , Proposed method, Gaussian-based dark channel , the problem in the image was caused by defogging to overcome this problem they used Fusion-based transmission estimation method combined with two different transmission models , The new fusion weighting scheme, the atmospheric light computed from the Gaussian-based dark channel and the flicker-free module. To get a complete defog image, the dehazing was combined with fusion weighting function and Vibe method was used to remove or reduce the flicker effect in the image.

TITLE	AUTHOR	ALGORITHM
An Efficient Fusion-Based Defogging	Jing-Ming, Guo, Jin-yuSyue, VincentRadzicki, HuaLee, Fellow.	Gaussian-based dark channel
Scene-Specific Pedestrian Detection for Static Video Surveillance	Xiaogang Wang, Meng Wang, and Wei Li	Confidence-encoded SVM
Quantifying and Transferring Contextual Information in Object Detection	Wei-Shi Zheng, Member, Shaogang Gong, and Tao Xiang	Context modelling, object detection
Vision in Bad Weather	Shree K. Nayar and Srinivasa G. Narasimhan	Chromatic Atmospheric Scattering
Contrast Restoration of Weather Degraded Images	Srinivasa G. Narasimhan and Shree K. Nayar	Fast algorithm

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(An ISO 3297: 2007 Certified Organization)

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Towards Fog-Free In-Vehicle Vision Systems through Contrast Restoration	Nicolas Hautière, Jean-Philippe Tarel/Didier Aubert	Contrast Restoration
Single Image Haze Removal Using Dark Channel Prior	Kaiming He, Jian Sun, Xiaoou Tang	Gaussian-based dark channel
Blind Haze Separation	Sarit Shwartz , Einav Namer and Yoav Y. Schechner	Polarization
Interactive (De)Weathering of an Image using Physical Models*	Srinivasa G. Narasimhan and Shree K. Nayar	interactive algorithms
A Fast Single Image Haze Removal Algorithm Using Color Attenuation	Qingsong Zhu, Jiaming Mai, Ling Shao	removal algorithms

Table-1: Algorithms used in Defogging

TITLE	AUTHOR	ALGORITHM
An Efficient Fusion-Based Defogging	Jing-Ming, Guo, Jin-yu Syue, Vincent Radzicki, Hua Lee, Fellow	Gaussian-based dark channel
Color image dehazing using the near-infrared	Lex Schaul, Clément Fredembach, and Sabine Süsstrunk	Gaussian-based dark channel
Image De-noising by Various Filters for Different Noise	Pawan Patidar, Sumit Srivastava	Gaussian-based dark channel
Underwater image dehazing using joint trilateral filter	Seiichi Serikawa, Huimin Lu	Gaussian-based dark channel
Under water image enhancement using guided trigonometric Bilateral filter and fast automatic color correction	Huimin Lu, Yujie Li, Seiichi Serikawa	Gaussian-based dark channel
Fast single image fog removal using the adaptive wiener filter	Kristofor B. Gibson and Truong Q. Nguyen	Gaussian-based dark channel
Improved Single Image Dehazing Using Dark Channel Prior and Multi-Scale Retinex	Bin Xie, Fan Guo, Zixing Cai	Gaussian-based dark channel
Multi-Scale Gaussian Normalization for Solar Image Processing	Huw Morgan , Miloslav Druckmüller	Gaussian-based dark channel

Table-2: The Gaussian-based dark channel is an algorithm used in image processing in different field.

III. DEFOGGING

Defogging means to remove the fog or moisture from an image. The defogging is caused because of unspecified light-source distribution or unsuitable mathematical constraints of the cost functions. The Gaussian-based dark channel uses the technique of the atmospheric light it gives the required amount of light to the camera to remove the fog from the image. Based on the Gaussian-based dark channel, the dehazing is accomplished through four major steps: atmospheric light estimation, transmission map estimation, transmission map refinement, and image reconstruction. The Confidence-encoded SVM is a combination of four transfer framework, the SVM is a detector used to detect the object in the surveillance by using the four frame works. Context modeling is also a frame work and they

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formulate polar geometric context, Tools used here are Pascal voc2005 and voc2007 data sets. The chromatic model derives several geometric constraints and develop algorithms for recovering a clear image. Fast algorithm is used to filter the noise with a naively estimated defogged image. Contrast Restoration is used to defog the image using fast algorithm and the removal algorithm. Polarization is a word used in physics, here polarization gives efficient light to remove the blind haze. Polarized are light waves in which vibration occur in single plane. Interactive method was proposed between degradation and the scene points which is based on dichromatic atmospheric model here it helps the degraded image to use atmospheric model to enhance the image. Removal algorithm easily estimates the transmission and restore the scene radiance with the atmospheric scattering model and does effectively removes the haze from the image.

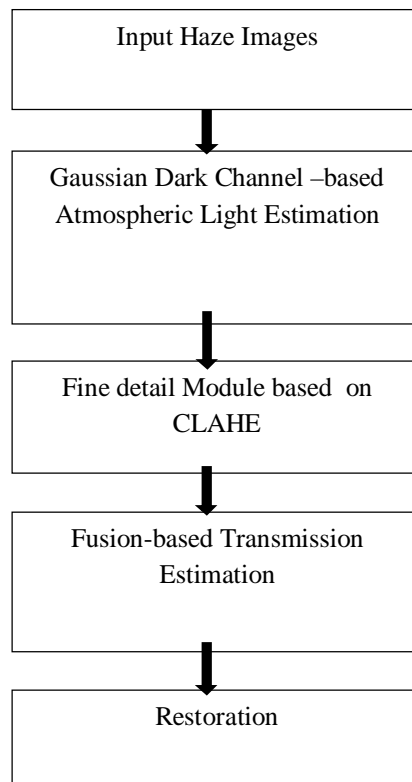


Fig-1: Flowchart of the proposed framework

IV. VARIOUS TECHNIQUES FOR DEFOGGING

A. Gaussian-based dark channel [10]:

Traditionally, the atmospheric light in is normally considered as the brightest pixel in the input image, assuming that there are no saturated pixels. However, this assumption is not valid in many practical cases. According to He's method, the atmospheric light can be correctly obtained through the selection of part of the brightness pixels in the dark channel of the normalized input.

$$I_{dark}(x) = \min_{y \in \Omega(x)} \min_{c \in \{r, g, b\}} I^c(y) / A^c$$

Where A^c and I^c denote the atmospheric light and the input hazy image of color channel c , respectively; $\Omega(x)$ is the local patch, and I_{dark} is the dark channel of I . However, for complicated scenes, this method, which includes two min operators, seems computationally expensive. For example, in Fig. 2(a), large white objects spread over the entire image. If we apply the original dark channel method directly to a large patch, the location as well as the value of the

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atmospheric light varies. Consequently, it degrades the accuracy of the atmospheric light model. To overcome this deficiency, a Gaussian-based dark channel I_{Gdark} is introduced

$$I_{Gdark}(x) = W(x) * M(x),$$

Where M denotes the minimum component of I , and $W(x)$ is the Gaussian function.

$$M(x) = \min_{c \in \{r, g, b\}} I^c(y).$$

$$W(x) = 1/\sqrt{2\pi\sigma^2} e^{-x^2/2\sigma^2}$$

Where $K = \max(\text{size}(I^c(y)))$

$$I_{Mdark}(x) = \min(W(x), M(x))$$

B. Context modeling [7]:

Assume we have a training set images of a target object class with the ground truth locations of the target objects in each image known. First, a detector is learned to model the object appearance which is called a base detector. In this paper the histogram of oriented gradients (HOG) detector is adopted, but any sliding window based object detector can be used. Second, the base detector is applied to all the training images to obtain a set of N candidate object windows (bounding boxes), denoted as $O = \{O_i\}_{i=1}^N$ which yield the highest scores among all candidate windows using the detector. Without loss of generality we let the first l candidate detections $O_p = \{O_i\}_{i=1}^l$ be true positive detections and the last $N - l$ detections $O_n = \{O_i\}_{i=l+1}^N$ be false positive ones. Let us denote the context corresponding to O_i by h_i and define $H_p = \{h_i\}_{i=1}^l$ and $H_n = \{h_i\}_{i=l+1}^N$. We call H_p the positive context set and H_n the negative context set. For our detection problem, we wish to compute the confidence of an object being the target object based on both its appearance and its visual context. Specifically, given an object O_i and its context h_i , the confidence of a candidate detection window containing an instance of the target object class is computed as:

$$D(O_i, h_i) = D_o(O_i) \cdot D_c(h_i), \quad (1)$$

where $D_o(O_i)$ is the prior detection confidence of an object being the target class obtained based on the output of the object appearance detector (base detector), $D_c(h_i)$ is the context score which is to be learned, and $D(O_i, h_i)$ is the posterior detection confidence which will be used to make the decision on object detection using context. In our work, $D_o(O_i)$ is computed based on the detection score of the base detector s_i ($\in (0, 1]$) parameterised by α as follows

$$D_o(O_i) = s_i^\alpha.$$

In the above equation, α determines the weight on the prior detection score s_i in computing the posterior detection confidence $D(O_i, h_i)$. More specifically, the higher the value of α , the more weight is given to the object appearance model which indicates that context in general is less useful in detecting the target object class. The value of α will be automatically estimated along with context quantification through learning, as described later. We wish to learn a context model such that the confidence $D(O_i, h_i)$ for true positive detections is higher than the false positive detections in the training set so that it can be used for detection in an unseen image. Before describing our context model in details, let us first describe how the context for the i -th candidate window h_i is computed.

a. A Polar Geometric Context Descriptor

Given a candidate object window O_c , we use a polar geometric structure expanded from the centroid of the candidate object to explore and represent the contextual information associated with the object detection window. With r orientational and $b + 1$ radial bins, the context region centered on the candidate object is divided into $r \cdot b + 1$ patches with a circle one at the center, denoted by $R_i, i = 1, \dots, (r \cdot b + 1)$. In this paper b is set to 2 and r is set to 16. The size of the polar context region is proportional to that of the candidate object window O_c . Specifically, the lengths of the bins along the radial direction are set to $0.5\sigma, \sigma$ and 2σ respectively from inside towards outside of the region, where σ is the minimum of the height and width of the candidate detection window O_c . Our polar context region bins have two key characteristics: 1) it can potentially represent many existing spatial relationships between objects and

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their context used in the literature, including inside, outside, left, right, up, down, co-existence. 2) The regions closer to the object are given bins with finer scale. This makes perfect sense because intuitively, the closer the context is, the more relevant it is, from which more information should be extracted. The polar context region is represented using the Bag of Words (BoW) method. These features are invariant to scale and robust to changes in illumination and noise. They are thus well suited for representing our polar context region. More specifically, given a training dataset, HOG features are extracted from each image and clustered into code words using K-means with K set to 100 in this paper. Subsequently for each bin in the polar context region outside the detection window of the candidate object, a normalized histogram vector is constructed, entries of which correspond to the probabilities of the occurrences of visual words in that bin. These histogram vectors are then concatenated together with the context inside the detection window which is represented using a single histogram vector to give the final context descriptor for the object candidate, denoted as the context associated to the object as described above by h_i . The high order information of the interaction between the context inside and outside of the detection window can then be inferred by the proposed selective context model as described in the next section. Note that with the proposed polar geometric structure for context modelling, context is always captured from adjacent regions of candidate object, and the potentially useful information in regions farther away may be neglected. There are a number of reasons for choosing the current setting: (1) for object detection in a surveillance environment where the scene background is fixed but objects presented in the scene are small, dynamic and are often in large numbers, the regions adjacent to each object detection window is more relevant. Importantly, in this case, including the regions farther away could have an adverse effect as all candidate object windows will have similar context in those regions which makes the task of distinguishing true detections from false positives harder. (2) Increasing the context regions size will also lead to the increase of computational cost during both training and testing. Nevertheless, it could in general be beneficial to explore contextual information from farther away regions when these information is not overly noisy. This can be achieved by simply increasing the context region size. Our polar context descriptor differs from alternative polar context descriptors, which also describe the context expanded from the center of the object, in that 1) Bag-of-Words method is employed for robustness against noise; 2) Pixels within context region need not be labelled; and 3) Context features are extracted more densely to cope with low image resolution and noise in our method. In contrast, only some predetermined sparse pixel locations were considered for context feature extraction in. The proposed contextual descriptor is also related to a number of existing descriptors for object appearance representation, including the shape context descriptor, the correlogram descriptor, the spatial pyramid representation and the spatial-temporal descriptor for describing pedestrian activity. In particular, as most polar geometric structure based descriptors, our descriptor is inspired by the shape context work of Belongie et al. The main difference here is that our descriptor is designed for context representation. It is thus centered at the candidate object location and captures contextual information from mainly the surrounding area of an object. Our context descriptor could incorporate the idea of correlogram to better capture the spatial co-occurrences of features cross different bins, although this would lead to an increase in computational cost. The works by Choi et al. would be a natural way to extend our context descriptor for modelling dynamic context for action/activity recognition. The spatial pyramid matching approaches which were originally formulated for object categorisation could be considered if we want to replace the exponent X^2 distance kernel (to be detailed next) used in our framework with a more sophisticated kernel.

b. Quantifying Context

Without relying on segmentation, our polar context region contains useful contextual information which can help object detection to different extents, as well as information that is irrelevant to the detection task. Therefore for constructing a meaningful context model, these two types of information must be separated. To that end, we introduce a risk function to evaluate and measure the usefulness of different contextual information represented using our polar geometric context descriptor. A context model is sought to utilise contextual information to leverage the prior detection score obtained using the base detector so that the posterior detection score of the true positive detection is higher than the false positives I . Specifically, the objective of context modelling is to minimize the following risk function with the positive and negative context sets H_p and H_n :

$$L = \sum_{h_i \in H_p} \sum_{h_j \in H_n} \delta(D(O_i, h_i) \leq D(O_j, h_j)),$$

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Note that the detection score of the base detector for a false positive detection window can be higher than that of a true positive window.

where h_i is the polar context descriptor corresponding to true positive detection windows as described in Section III-A, h_j is the context descriptor corresponding to the false positives, and δ is a Boolean function with $\delta(\text{true}) = 1$ and 0 otherwise. This risk function measures the rank information between true positives and false positives. The smaller the value of the risk function is, the more confident the detection would be for unseen data. In order to compute the posterior detection score $D(O_i, h_i)$ defined in Eqn. (1), we need to compute both $D_o(O_i)$ and $D_c(h_i)$. $D_o(O_i)$ is obtained by Eqn. (2), and we compute $D_c(h_i)$ as

$$D_c(h_i) = \exp\{f(h_i)\},$$

Where $f(h_i)$ is a leverage function that outputs the confidence score of the context descriptor h_i , and the higher the value of f is the more positive the contextual information is. We consider to learn the leverage function f as a kernel linear function:

$$f(h_i) = w^T \phi(h_i) + b$$

Where ϕ is a nonlinear mapping implicitly defined by a Mercer kernel κ such that $\phi(h_i)^T \phi(h_j) = \kappa(h_i, h_j)$. Kernel trick is used here because the descriptor we introduce (i.e. a histogram) is a distribution representation of high dimension; the exponent X2 distance kernel, which is a Mercer kernel, can thus be used to measure the distance between two discrete distributions. Note that the variable b in does not have any impact on the risk function up to now, but it will be useful for learning a much better w in an approximated way. This is because a more flexible solution for w can be found by utilizing b at the training stage, as we shall describe next

$$L = \sum_{h_i \in H_p} \sum_{h_j \in H_n} \delta(s_{ai} \cdot \exp\{f(h_i)\} \leq s_{aj} \cdot \exp\{f(h_j)\}),$$

The ideal case to minimize the risk function in Eqn. (6) is to learn a leverage function f fulfilling all the following constraints:

$$s_{ai} \cdot \exp\{f(h_i)\} > s_{aj} \cdot \exp\{f(h_j)\}, \forall h_i \in H_p, h_j \in H_n.$$

Directly solving this problem is hard if not impossible and would also be a large scale optimization problem. For example, if $\#H_p = 100$ and $\#H_n = 100$, there will be 10000 inequalities for consideration. Therefore, an approximate solution is required. By taking logarithm on both sides of Eqn. (7), we approach the problem of minimizing the risk function by investigating a solution constrained by a margin $\rho (\geq 0)$ as follows:

$$\begin{aligned} f(h_i) + \log s_{ai} &\geq \rho, \forall h_i \in H_p, \\ f(h_j) + \log s_{aj} &\leq -\rho, \forall h_j \in H_n. \end{aligned}$$

Ideally, that would be satisfied if the above constraints are valid. For approximation, we would like to learn the function such that the margin ρ is as large as possible. Therefore, we aim to find the optimal w , b , and α that ρ is maximized (or $-\rho$ is minimized) as follows:

$$\begin{aligned} \min & -\rho \\ \text{S.t.} & w^T \phi(h_i) + b \geq \rho - \log s_{ai}, \forall h_i \in H_p, \\ & w^T \phi(h_j) + b \leq -\rho - \log s_{aj}, \forall h_j \in H_n, \rho \geq 0. \end{aligned}$$

Note that without regularization, the margin ρ can be made as large as possible by simply scaling w , b , and α in the above criterion. In order to avoid this problem, for non-negative v and C , we introduce the following regularized criterion:

$$\begin{aligned} \{w, b, \alpha\} &= \arg \min w, b, \alpha \rho - v \cdot \rho + 1/2 (\|w\|^2 + C2 \cdot \alpha^2) + 1/NN \sum_{i=1} \xi_i \\ \text{S.t.} & w^T \phi(h_i) + b \geq \rho - \xi_i - \log s_{ai}, \forall h_i \in H_p, \end{aligned}$$

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$$w^T \phi(h_j) + b \leq -\rho + \xi_j - \log s_j, \forall h_j \in H_n,$$

$$\rho \geq 0, \xi_i \geq 0, i = 1, \dots, N,$$

Where positive slack variables $\{\xi_i\}_{N_i=1}$ are additionally added to the margin ρ for each constraint, because completely satisfying all the constraints without the slack variables in model (10) would be very difficult. With the criterion above learning our context model becomes a constrained quadratic programming problem. Next, we show that we can reformulate the problem so that the popular SVM technique can be used to find the optimal solution. Let $\alpha' = C \cdot \alpha$ and define $z = [w^T, \alpha']^T$ and $\psi_C(h_i, s_i) = [\phi(h_i)^T, \log s_i]^T$, rewritten the formula as,

$$\{z, b\} = \arg \min z, b, \rho - v \cdot \rho + \|z\|^2 / 2 + 1 / N \sum_{i=1}^N \xi_i$$

$$\text{s.t. } z^T \psi_C(h_i, s_i) + b \geq \rho - \xi_i, \forall h_i \in H_p,$$

$$z^T \psi_C(h_j, s_j) + b \leq -\rho + \xi_j, \forall h_j \in H_n,$$

$$\rho \geq 0, \xi_i \geq 0, i = 1, \dots, N.$$

Now any SVM solver such as can be used to learn the model parameters w , b , and α . Note that with the formulation above, a new mercer kernel κ' for ψ_C can be defined as $\kappa'(\{h_i, s_i\}, \{h_j, s_j\}) = \kappa(h_i, h_j) + C \cdot 2 \cdot \log s_i \cdot \log s_j$. In this work, for the two free parameters C and v , we set $C = 1$ and estimate the value of v using cross-validation. We refer the above model as the maximum margin context model (MMC). It utilises the prior detection results obtained by a sliding window detector (s_i) and enables the model to selectively learn useful discriminant context information so that the confidence of those marginal true positive detections are maximised conditioned on the prior detection confidence. After selecting and quantifying contextual information using the MMC model, a posterior detection confidence score for a candidate detection O_i in a test image is computed as:

$$D(O_i, h_i) = D_o(O_i) \cdot D_c(h_i) = \text{sat } i \cdot \exp \{w^T \phi(h_i) + b\}.$$

Context aware object detection can then be performed on a test image by thresholding the posterior detection confidence score for each candidate window. It should be noted that when a linear kernel is used the proposed MMC can be seen as a feature selector for the simple concatenation of detection score and contextual features. However, since the detection score and the contextual features are lying in different spaces or manifolds, the linear kernel is not a suitable similarity measurement for such kind of combination. Hence, the nonlinear exponent X2 distance kernel is adopted to measure the similarity between histogram based contextual features. Comments on α . intuitively for different target object classes, contextual information has different levels of usefulness in disambiguating the target object class from background and other object classes. For instance, context is much more important for an object class with very diverse appearance but always appearing with a fixed surroundings than one that has uniform appearance but can appear anywhere. As mentioned earlier, the value of α in our MMC model, which is learned from data, indicates how important context information in general is for detecting the target object class. This is different from the model parameter w which corresponds to the relevant importance of different high order context information with regard to each other. Specifically, $\alpha = 0$ means that the prior probability would not have any effect on the maximum margin model and should also be ignored in the risk function and the posterior detection score. For $\alpha > 0$, the larger it is, the more important the prior detection probability is and the less useful the contextual information in general will be. In particular, a very large α value will mean the contextual information is completely discarded. Note that the value of α is not restricted to be non-negative. When α has a negative value, the smaller the prior detection probability is, the larger the posterior detection score is expected. This is because $s_i \in (0, 1]$ and the leverage function $f(h_i)$ is always bounded by investigating the dual problem formulated. Although theoretically possible, it is unlikely that a negative value of α will be obtained in practice unless a poor base detector is used which completely fails to capture the object appearance information.

C. Confidence-encoded SVM [8]:

Negative Samples from Vehicles It is unreliable to directly count windows detected on vehicle paths as negative samples, since some pedestrians and bicycles also move on vehicle paths. To select confident negative

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samples, the existence of moving vehicles need to be first detected. It is achieved by feature point tracking and clustering. Feature points are detected and tracked using the KLT tracker. Stationary points

This Algorithm has done earlier

Input:

The current detector ($w_0; b_0$)

The source dataset D^s

The target dataset D^t

The initial confidence scores of target samples c_0

Output:

The scene-specific detector ($w_u; b_u$)

$v \leftarrow \Psi(D^s; D^t; c_0)$

$k = 0$

Repeat

$k \leftarrow k + 1$

$C_k \leftarrow \text{argmin} G(c; w_{k-1}; b_{k-1}; c_0; v; D^s; D^t)$

$(W_k; B_k) \leftarrow \text{argmin}_w; bG(c_k; w; b; c_0; v; D^s; D^t)$

Until Converge

$(W_u; b_u) \leftarrow (w_k; B_k)$

And short trajectories are removed. Then trajectories are clustered based on temporal and spatial proximity by mean shift. Each trajectory cluster is assigned to a vehicle path or removed based on the spatial overlap between the cluster and the path. The remaining trajectory clusters mainly correspond to vehicles. The size range of vehicles along each vehicle path is estimated using mean shift. The trajectory clusters of pedestrians on vehicle paths are removed using the size evidence. If a detection window is on a trajectory cluster which is on a vehicle path and whose size is large enough, the detection window is selected as a confident negative sample.

V. CONCLUSION

To propose an accurate model for the estimation of the atmospheric light patterns the traditional method and the new physics method is also proposed. In this paper there are different ways of algorithms and methods have used to defog the image, the mainly used algorithm is dark channel where it helps to filter the image and the image is fog free after the dark channel prior is applied. Defog is occurred under climatic conditions where the light source is not sufficient for the camera and it cannot capture the moving object in the surveillance thus the different techniques are used to defog/dehaze the image.

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ISSN(Online): 2319-8753
ISSN(Print): 2347-6710

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

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