Eigen analysis and gray alignment for shadow detection applied to urban scene images

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***Abstract*— Urban scene analysis is very useful for many intelligent transportation systems (ITS), such as advanced driver assistance, lane departure control and traffic flow analysis. All these systems are prone to any kind of noise, which ultimately harms system performance. Considering shadow as a noise problem, this may represent a critical line between the success or fail of an ITS framework. Therefore, shadow detection usually provides benefits for further stages of machine vision applications on ITS, although its practical use usually depends on the computational load of the detection system. To cope with those issues, a novel shadow detection method, applied to urban scenes, is proposed in this paper. This method is based on a measure of the energy defined by the summation of the eigenvalues of image patches. The final decision of an image region to contain a shadow is made according to a new metric for unsupervised classification called here as gray alignment. The characteristics of the proposed method include no supervision, very low computational cost and mathematical background unification, which turns the method very effective. Our proposed approach was evaluated on two public datasets.**

I. INTRODUCTION

While we need light to see the world, shadows come to our eyes as an inevitable effect. When light casts shadow over objects in a scene, shadow projections (umbra and penumbra) on an image plane can bring either useful or useless information. In the field of intelligent transportation systems (ITS), as the aim is to develop advanced machine vision applications, such as video surveillance, advanced driver assistance or traffic flow analysis, shadow detection usually provides benefits for further stages of ITS frameworks. Just to cite an example, object detection systems (ODS) rely on features and classifiers in order to say where an object is located in an image [1]; in this case, shadows can harm ODS work, leading them to take shadows of objects as objects of interest.

Recognizing image shadows still remains an open and extremely challenging problem. In ITS field, we can cite that Prati et al. [2] have classified existing approaches to detect shadows in images as statistical and deterministic, according to the nature of the classification algorithms. After [2], algorithms which rely solely on statistical methods can still be categorized as parametric [3] or non-parametric [7], while the deterministic ones are based on model [8] or non-model [9]. Although in [2], the goal was to compare shadow detection methods based on moving techniques (i.e., applied on videos, and taking the temporal information in favor), the proposed taxonomy fully spans all the categories of classification methods used so far, whether on video or still images. There are two points worth noting here: we are particularly interested on still natural scene images, exploring spatial information rather than temporal one; and, although our method was conceived by means of a non-supervision framework, (and, then, it would be classified as a non-model based, deterministic approach), it cannot be seen as a learning driven method. Conversely, the proposed method described here can be described as a unified mathematical-grounded method to recognize shadows, in a very fast way. Particularly in traffic flow analysis, interests go to moving cast shadows, since it can aid in a more accurate vehicle detection; this is the case of Hsieh et al. [4], who tackle the problem of vehicle occlusions, detecting and removing moving cast shadows. For a survey of moving shadow algorithms, refer to [5].

For generic shadow detection systems, recent methods pervasively use learning to classify shadow and non-shadow image pixels, trying to tackle the problem as a composition of many different features and classifiers. For example, Zhu et al. [10] proposes a conditional random field (CRF) based system to detect cast shadow in natural scenes; there, CRF is integrated to boosted decision tree classifiers, and its parameters are learnt by a Markov random field (MRF); all classifiers run over a set of feature types, with the goal of capturing all possible shadow information in grey level images. Guo et al. [11] presents a shadow detection method based on statistics of pair-wise regions; the proposed method relies on computing illumination components from color (using LAB and RGB color spaces) and texture in each region, and comparing similar and different illumination pairs; the inference over the image regions are accomplished by means of a graph-cut based optimization. Lalonde et al. [12] describes a method which explores the local cues of the image shadow; local features are used to reason over boundaries and edges, and to create a set of shadow cues to be classified by a CRF and a decision tree. All of these works use color images, but Zhu et al. and our work.

Differently from all, our work does use neither special features, nor any learning method to decide between shadow and non-shadow. Instead, our energy-based proposed method represents a unified view which detects shadows at a glance,

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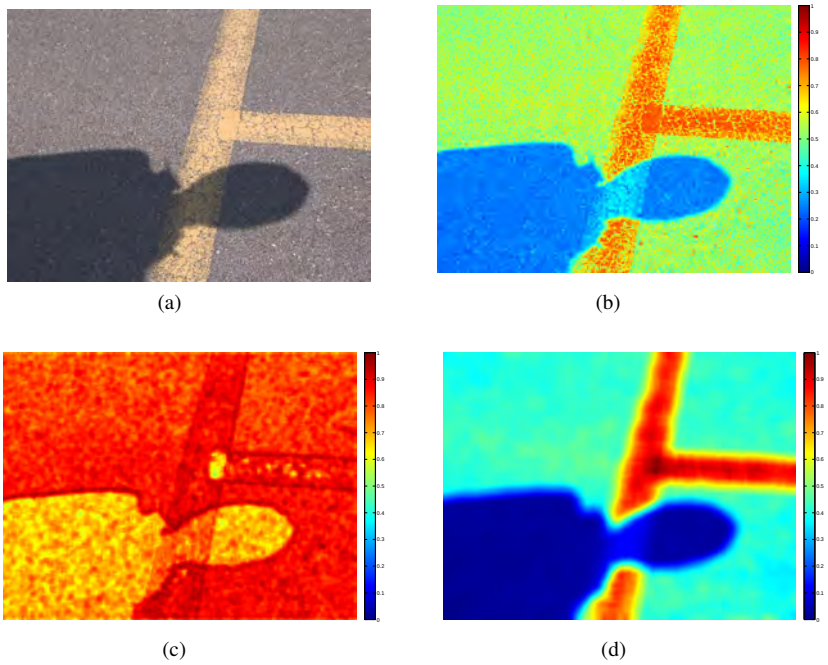


(a) (b) (c) (d)

Fig. 1: Eigenvalue-based energy function. (a) Original image. (b) Heat map of the original image. (c) Heat map of the entropy of the original image. (d) Heat map of the summation of the eigenvalues of image patches. Note that the heat map of the eigenvalues (d) highlights shadow region in the same way that the heat map of the entropy (c) does, which demonstrates the characteristics selected by the eigenvalue-based energy function.

just using algebraic operations over image eigenvalues. For that, we compute the summation of the eigenvalues on image patches, making decisions if a pixel is shadow or non-shadow based on the similarity of its color channels. After [6], pixels owing to cast shadow regions have its RGB components inside a symmetry axis corresponding to the background; such analysis leads to a geometric interpretation to the problem and represents a weak classifier. As in [6], we have adopted a geometric analysis, which searches for similarities in the color channels in regions of low energy in the scene. We call this task as gray alignment. Following this approach, we have achieved a state-of-the-art performance over a subset of [11]'s dataset with urban natural scenes, and over a subset of [5]'s dataset (Highway I).

The motivation to use eigenvalues is twofold: i) darker objects usually have high entropy than lighter objects, however shadowed objects (which is dark for our view) present low entropy, which distinguishes them as a shadow; ii) on the other hand, entropy filters are computationally heavy, and, by computing the eigenvalues, we can save time in a robust shadow detection. In conclusion, with an eigenvalue-based energy function, one has lighting intensity and gradient analyses all at once in a unified method to spatially detect shadow. Figure 1 illustrates these ideas; in Figs 1b-1d, the lighter objects represents shadows, while hotter objects represents the rest of the image. Shadow regions is best selected in Fig. 1d.

II. Eigenvalue-based energy function

A. Definition of the proposed energy function

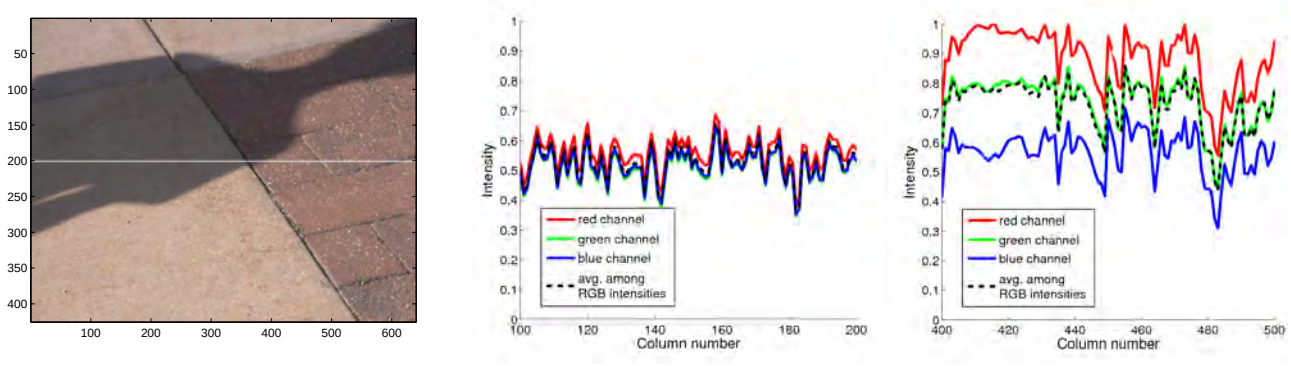
Let M be the normalized gray-level image from the RGB image I. We can state that shadow areas of M present low light intensity, small spatial gradients and low entropy, that is, they present low magnitudes with small spatial fluctuations if compared to lit image regions. Our goal is to find a function which measures the energy distribution over the image according to the characteristics above. Using that function, we will be able to segment shadow regions of M by means of the eigenvalues of the image subregions (patches). For that, we will use the Gerschgorin's circles theorem [13] below.

Theorem 1: The eigenvalues of $Q \in \mathbb{C}^{n \times n}$ are contained in the union of the n Gerschgorin's circles defined by $|z - q_{ii}| \leq r_i$, where

$$r_i = \sum_{\substack{j=1 \\ j \neq i}}^{n} Q(i,j)$$

for $i = 1, 2, ..., n$.

After Gerschgorin[13], if a matrix presents small magnitude elements and small fluctuations in these magnitudes, so its eigenvalues also present small magnitudes if compared to a same size matrix which contradicts those preconditions. Thus, if we find relatively small subregions in M, we are able to classify such small regions as shadow or non-shadow, without the need of a spatial analysis of texture, color or



(a) (b) (c)

Fig. 2: Color intensity over the white line in the original image (a). Note the approximation among R, G, B intensities in the shadow areas in contrast to lighter image regions (c)

gradients. This is possible since we are measuring, all-at-once, the light intensity and spatial variation of that small image region. Next, we present how we define our energy-based function based on the aforementioned ideas.

Let us define S as a matrix whose elements will be calculated as

$$S_{ij} = f(\lambda_1(A^T A), \lambda_2(A^T A), ..., \lambda_n(A^T A)), \quad (1)$$

where A, of order n, is a square submatrix of M, whose central element is located on the coordinates (i, j), and f is a function of the eigenvalues λ_k, $k = 1, ..., n$, of $A^T A$ (the product $A^T A$ was used to avoid complex eigenvalues that could turn complex the computation of f). It is noteworthy that n is odd (further, this constraint will be relaxed).

If we define f as a multiplication operator among the eigenvalues of $A^T A$, then we have $S_{ij} = det(A^T A)$. In this case, if any eigenvalue of $A^T A$ is nil, S_{ij} is also nil. Furthermore, S_{ij} will have a nil value if rows or columns are equals in $A^T A$. In practice, shadows regions can imply nil eigenvalues, but it does not suffice to say that nil eigenvalues imply shadow areas. This is a common situation in very light image regions, and hence f cannot be considered as a multiplication operator.

Even knowing that the eigenvalues of $A^T A$ are all real, it is impossible to guarantee that all values are not nil, and thus S_{ij} cannot simply be a division relation among the eigenvalues of $A^T A$. A simple and coherent choice for f is a summation, since S_{ij} will be nil if and only if all eigenvalues of $A^T A$ is nil. Because of all elements of A is non-negative, the result of the summation will never be negative. According to that, we can redefine S as

$$S_{ij} = \sum_{k=1}^{n} \lambda_k(A^T A). \quad (2)$$

Note that this new S can have a high computational cost to be computed, since all operations are pixel-wise over M. This high cost becomes inevitable for high values of n. To solve this problem, let us define $A_{n\times n} = (v_1\ v_2\ \dots\ v_n)$ where $v_k = (a_{1k}\ a_{2k} \dots\ a_{nk})^T \in \mathbb{R}^n$ and $k = 1, 2, \dots, n$. Then, we have

$$A^T A = \begin{pmatrix} v_1^T v_1 & v_1^T v_2 & \dots & v_1^T v_n \\ v_2^T v_1 & v_2^T v_2 & \dots & v_2^T v_n \\ \vdots & \vdots & \ddots & \vdots \\ v_n^T v_1 & v_n^T v_2 & \dots & v_n^T v_n \end{pmatrix}. \quad (3)$$

From (3), we can write S as

$$\begin{aligned} S_{ij} &= Trace\left(A^T A\right) \\ &= \sum_{k=1}^{n} v_k^T v_k \\ &= \sum_{k=1}^{n} \|v_k\|_2^2. \end{aligned} \quad (4)$$

Following this approach, let A be a subregion of M, centered in a pixel located in (x, y) and $Q = A^T A$ (with that, we guarantee that all eigenvalues of Q are real). In order to increase the precision of our detector, we have associated the summation of the eigenvalues of Q to a temporary matrix E, defined as

$$\begin{aligned} E_{xy} &= \sum_{k=1}^{n} \lambda_k(Q) \\ &= \sum_{k=1}^{n} \lambda_k(A^T A) \end{aligned} \quad (5)$$

B. Gray alignment-based unsupervised classifier

Figure 2 illustrates the phenomenon of shadow occurrence on a surface. Note that each RGB channel over a pixel becomes closer to the mean of RGB intensities, that is, there is an alignment between the color vector ($\vec{C}$) and mean color ($\vec{p}$) defined as

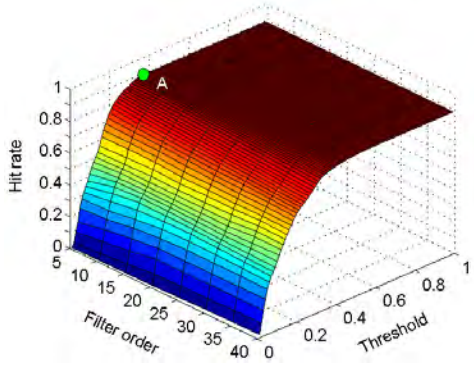


Fig. 3: Determining the best threshold in function of the filter order (point A, $threshold$ = 0.39 and matrix order of 5).

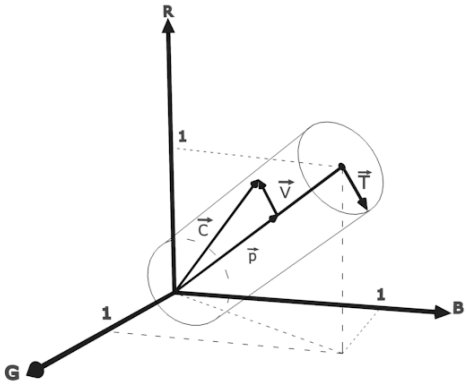


Fig. 4: Geometric interpretation of gray alignment. Any point out of the cylinder of radius equal to $\vec{T}$ is automatically deemed as non-shadow.

$$\vec{C} = R\hat{r} + G\hat{g} + B\hat{b} \tag{6}$$

$$\vec{p} = \mu(\hat{r} + \hat{g} + \hat{b})\,, \tag{7}$$

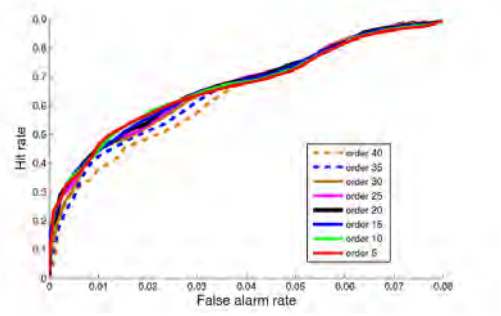
where

$$\mu = \frac{R+G+B}{3}\,. \tag{8}$$

This is equivalent to a saturation reduction of the color in badly lit regions. Figure 4 depicts the geometric interpretation of the gray alignment principle, indicating a cylinder around the line $R = G = B$, where out of that, no combination of colors indicates that a pixel belongs to a shadow area. Still according to Figure 4, we have that $I(x, y)$ belongs to a shadow area if, and only if, the associated color to $I(x, y)$ is contained inside the cylinder of radius equal to $|\vec{T}|$. Algebraically, it is given by

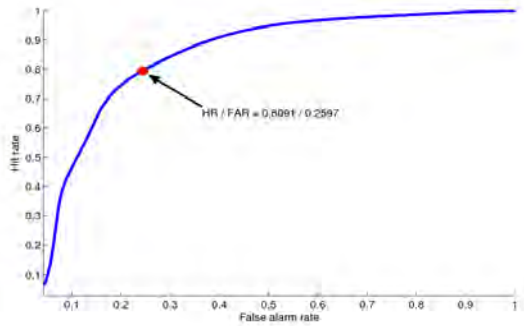
$$\vec{c}_{shadow} \Longrightarrow |\vec{V}| = |\vec{C} - \vec{p}| < |\vec{T}| \tag{9}$$

In order to minimize the computational load of Eq. (9), we rewrote it as



(a)

Fig. 5: ROC curves on a subset of [10]'s dataset. There is no significant impact on the detection performance by varying the filter order. In FAR = 7%, HR = 89%.



(a)

Fig. 6: ROC curves on a subset of [5]'s dataset (Highway I). The operating point corresponds to 80.91% of hit rate (HR) and 25.97% of false alarm rate (FAR).

$$|R \cdot G \cdot B - \mu^3| < |\vec{T}|\,, \tag{10}$$

where the operation in the equation is pixel-wise.

For a pixel to be considered within a shadow area, it needs to attend the required conditions of the gray alignment classifier, and must have its energy level bellow a certain value, according to the eigenvalue-based energy function. Based on our experimental analyses, the best threshold for the eigenvalue-based function was found to be 0.39 and $|\vec{T}|$ was 0.005.

III. Result Analysis

Our method requires just two parameters: the order n of the sub-matrices and the threshold to binarize the image as shadow or non-shadow. To determine the best threshold to our classifier, the surface in Figure 3 was built by varying the filter order (equivalent to the size of the image patch to calculate the eigenvalues) and the threshold, in the interval $[0, 1]$, of the classifier defined in 10. This is found in point A in the figure.

To evaluate the performance of the proposed system, two datasets were used: a subset of [10]'s dataset with 39 images of urban scenes, and a subset of [5]'s dataset with 80 images.

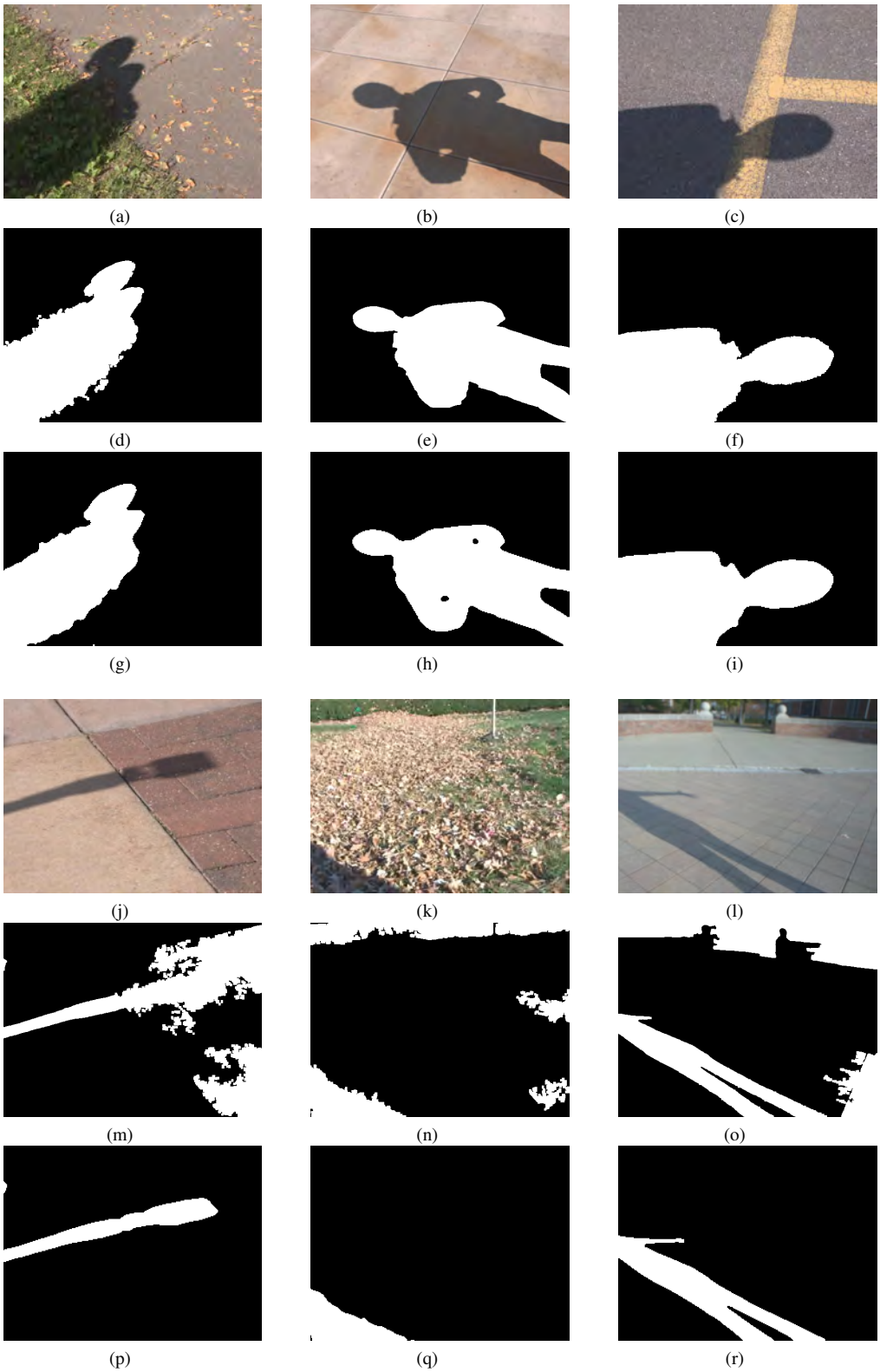


Fig. 7: Detection examples. **(a-i) near perfect detections:** First line (a-c), original images; second line (d-f), detection results; third line (g-i), ground truth. **(j-r) bad detections:** First line (j-l), original images; second line (m-o), detection results; third line (p-r), ground truth.

Shadow detection	Shadow	Non-shadow
Shadow (GT)	**0.7498**	0.0838
Non-shadow(GT)	0.2502	**0.9162**

TABLE I: Confusion matrix of the detector with approximately 75% of shadow detection and 92% of non-shadow detection.

Figure 5 shows the ROC curve of our shadow detector over [10]'s dataset. It is noteworthy that even varying the eigenvalue matrix order (filter order), there was no significant improvement in the detection performance. It indicates that a lower matrix order can be more suitable in terms of computation speed, since it reduces significantly the number of operations to compute the summation of the eigenvalues. Table I summarizes the confusion matrix with approximately 75% of shadow detection and 92% of non-shadow detection over the [10]'s dataset.

Figure 6 shows the ROC curve of the proposed method over a subset of [5]'s dataset (Highway I). The annotation was remade since we did not find the original one. In view of that, only the cast shadows (or those ones completely projected on the ground) were considered. One important fact which came with that choice was the method to make mistakes over the shadows detected over the vehicles (see Fig. 8). Even though, it was achieved approximately 81% of hit rate.

In Figure 7, there are some examples of the resulting images after the detection over [10]'s dataset: Figures 7 (d)-(f) show some near perfect results, while Figures 7 (m)-(o) show bad results. The bad results can be explained by the detection of some penumbras in some sparse regions of the image which were not annotated. In Figure 8, some resulting images after performing the method over the subset of [5]'s dataset are depicted. Annotation of the images of Highway I's dataset was performed considering only the cast shadow, and it is noteworthy that shadows on the cars (form shadows) represent detection mistakes (in practice, it is something should also be removed as shadow).

IV. Conclusion

This paper has presented a novel method for image shadow detection, based on eigenvalue-based energy function and gray-level alignment classification. The motivation of the use of eigenvalues over a matrix of the kind $A^T A$, where A is an image patch, is grounded on the fact that: i) darker objects usually have high entropy than lighter objects, although shadowed objects (which is dark in the image) presents low entropy, which distinguishes them as a shadow; ii) entropy filters are computationally heavy, and, by computing the eigenvalues, we can save time in a robust shadow detection; an eigenvalue-based energy function presents then a clear distinction between lighting intensity and gradient information all at a time, providing a unified method to spatially detect shadow. Our proposed method have demonstrated to own very low computational cost, to be unsupervised, and to perform very efficiently over a subset of a public dataset.

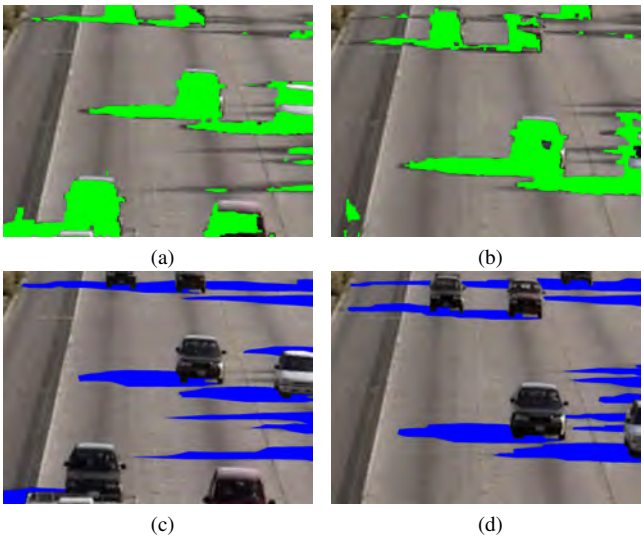


Fig. 8: Results on [5]'s dataset (Highway I). First line (a-b), shows detection results, while second line (c-d) shows the annotations.

Future work goes toward the integration of the method in a temporal framework.

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