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Automatic Urban Road Segmentation

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Abstract

Automatic road segmentation is important for many vision-based traffic applications, such as traffic surveillance, traffic flow measurement, and incident detection. Road segmentation provides useful information for precluding from further consideration the objects and activities appearing outside road areas. The proposed method, using fuzzy-shadowed set operations, consists of four major steps: background image generation, foreground object extraction, background pasting, and road localization. The experimental results reveal that the proposed method can effectively detect road areas under different environmental conditions.

Keywords: Road segmentation, Background pasting, Road localization, Fuzzy-shadowed sets

1. Introduction

Road condition detection is an important task with many applications, and one major category is road extraction from airborne SAR (Synthetic Aperture Radar) images and remotely sensed images. The techniques commonly employed in this category include model-based approaches (Katartzis, Sahli, Pizurica, & Cornelis, 2001), genetic algorithms (Joen, Jang, & Hong, 2002), neural networks, and fuzzy clustering methods (Dell'Acqua, & Gamba, 2001). Another important category is road extraction from traffic images for such applications as traffic surveillance (Kamijo, Matsushita, Ikeuchi, & Sakauchi, 2000; Wang, Tsai, Chung, Chang, & Chen, 2004a), traffic flow measurement (Taipei Traffic Engineering Office, 2005; Wang, Tsai, Chung, Chang, & Chen, 2004b), traffic accident/incident detection (Lim, Choi, & Jun, 2002), vehicle guidance (Ma, Lakshmanan, & Hero, 2000), and driver assistance (Kaliyaperumal, Lakshmanan, & Kluge, 2001). Since traffic events typically occur on road areas, road segmentation provides a priori information for precluding from further consideration the objects, events and activities emerging outside road areas. This not only prevents interference by irrelevant objects, activities and events but also reduces the processing time.

The techniques of road segmentation developed for traffic applications can be further divided into two classes, one for static traffic images and the other for dynamic traffic images. Static traffic images are acquired by a camera with the fixed parameters of focal length, tilt, roll and panning angles, so static images will contain the same background of the scene.

Traffic applications based on static images include traffic flow measurement, traffic monitoring, and traffic accident/incident detection. However, dynamic images contain different backgrounds. The associated applications include driver assistance, vehicle guidance and automatic navigation.

The proposed road segmentation method consists of four major steps: background image generation, foreground object extraction, background pasting, and road localization. In the first step, the background image of the scene is generated using a histogram-based progressive technique. The generated background image is used in the second step to quickly extract foreground objects from each input video image. The background patches corresponding to the extracted foreground objects are pasted onto an image, called the road image. Repeating the second and the third steps for each input image, a major component of the road region will gradually be constructed. To obtain the full road region, two more tasks hole filling and road localization must be completed. The first of these tasks is accomplished by invoking a morphological process and the second is achieved using a fuzzy-shadowed set theoretic technique.

In this paper, we develop automatic road extraction from static urban traffic images. The proposed technique is addressed in Section 2, which presents several important components of our technique. Afterwards, experimental results and discussion are presented in Section 3, followed by concluding remarks and suggestions for future work in Section 4.

2. Road segmentation process

Figure 1 depicts a block diagram for the proposed road segmentation process. There are four major steps constituting the process: background image generation, foreground object extraction, background pasting, and road localization. As mentioned, static traffic images are considered. They contain the same background of a scene. To begin, we generate the background image of the scene using a histogram-based progressive technique. This technique was previously described in Chung, Wang, & Chen (2002). Unlike many previous techniques that required large storage space to preserve image sequences for batch background image generation, our method uses histograms to record and trace the intensity changes of pixels, thus greatly reducing the required storage. Furthermore, our method progressively generates and updates the background image, so intermediate results of the background image can be provided at any instance of time during generation. The details of our background image generation technique can be found in.

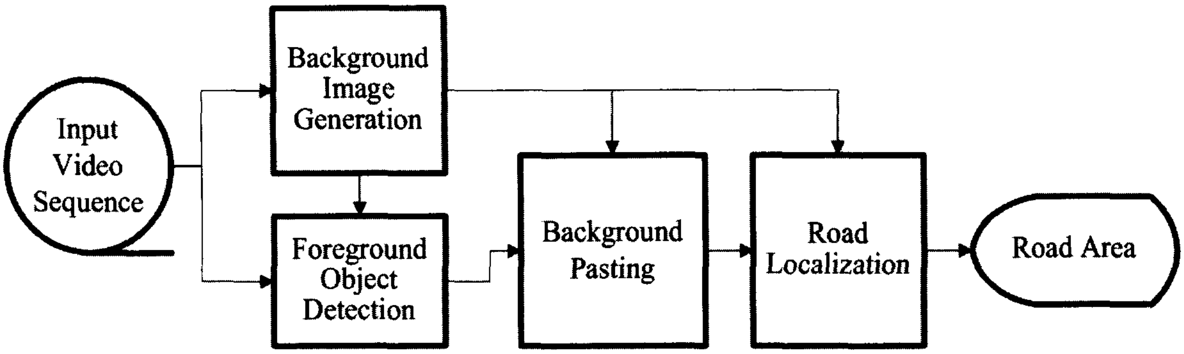


Figure 1. Block diagram for road segmentation.

The generated background image is then used to quickly extract foreground objects from each input video image. A simple image differencing method is employed for foreground object extraction. The extracted objects may be of interest or of no interest. By objects of interest, we refer to the objects appearing within the road area. Interesting objects will directly contribute to road segmentation. However, uninteresting objects will not harm to the final result of road segmentation. We do not attempt to discriminate between interesting and uninteresting objects at this point so as to greatly reduce the complexity of this step. Actually, the fuzzy concepts involved in the final step play an important role in resolving this issue of uncertainty. In addition, the issues of imprecision, vagueness and in- consistency ubiquitous throughout the process are all left to the last step to be resolved. We compensate for noises by applying morphological operations and connecting component labeling.

The background patches corresponding to the foreground objects extracted from each video image are cumulatively pasted in an image, called the road image. The steps of foreground object extraction and background pasting are repeated for each input image. Eventually, a major component of the road area will be constructed. To recover the full road region hole filling and road localization must be completed. The first of these tasks is accomplished by invoking a morphological process and the second task is achieved using a fuzzy-shadowed set theoretic technique. Note that the result of every step is inevitably imperfect. Fuzzy sets have been well known to provide an effective tool for modeling imprecision, vagueness, inconsistency, and uncertainty. The final step of road localization conceptualized by fuzzy disciplines will compensate for these issues.

In the following sections, we detail the steps of foreground object extraction, background pasting and road localization.

2-1. Foreground object extraction

Let $I(t)$ be the input video image at time t. By comparing it with the background image $B(t)$, we obtain foreground image $F(t)$. Mathematically,

$$F(t): \{(x, y) \mid |i(x, y) - b(x, y)| \geq \tau,\ i(x, y) \in I(t),\ b(x, y) \in B(t)\}, \quad (1)$$

where x, y are the coordinates of images, and τ is a small threshold value, which may be varied in different outdoor conditions (Chen, Chung, Liu, Cherng, & Chen, 1998). To eliminate superfluous noises in the foreground image, morphological operators (Gonzalez & Woods, 2002), *closing* and *opening* operators, are applied. During noise removal, a small rectangular mask with the size of 2-by-3 or 3-by-2 is employed as the morphological structure element. Afterwards, a connected component labeling process is applied to further eliminate medially large noisy components. The process is also implemented using morphological operations characterized by the eight-connected definition (Gonzalez & Woods, 2002). Specifically, the process starts with a point $p(x, y)$ of an unknown component Y contained in $F(t)$, this component would be extracted through iterating the following morphological process.

$$X_k = (X_{k-1} \oplus B) \cap F(t), \quad (2)$$

where $\oplus$ is a dilation operator; in which the initial value $X_0 = p(x, y)$; and k is the iteration index, initially set to 1. B is the structure element of size 3-by-3 with its origin located at the center of the element. This algorithm iterates until it converges to $X_k = X_{k-1}$. The extracted connected component is X_k i.e., $Y = X_k$.

2-2. Background pasting

Let $F(t)$ be the set of foreground objects extracted from $I(t)$ and $B'(t)$ be the set of background patches corresponding to $F(t)$. The background patches determined at each time are pasted on an image R, called the road image.

$$R = \bigcup_{1 \leq i \leq t} B'(i). \quad (3)$$

If t is large enough, a major part of the road area will be constructed in R. However, there may be holes and noises present in the recovered road area. A morphological hole filling process (Gonzalez & Woods, 2002) is applied to the recovered road area. This process starts with a point $p(x, y)$ of the recovered road area. The holes inside the area are gradually filled by iterating the following process.

$$X_k = (X_{k-1} \oplus B) \cap R^c, \quad (4)$$

where R^c is the complement of R. In which the initial value $X_0 = p(x, y)$, and k is the iteration index initially set to 1. B is a symmetric structure element of size 3-by-3 with its origin at the center of the element. This above algorithm iterates until it converges to $X_k = X_{k-1}$. The result of hole filling is X_k. Note that Eqs. (2) and (4) may be different according to the definition of structure element B.

2-3. Road localization

After filling the holes within the recovered road area, we need to further locate its boundary in order to obtain the whole road region. However, there may be undesirable areas, which originated from uninteresting objects, as mentioned above. In addition, the recovered road area has been corrupted with imperfections, such as imprecision, vagueness and uncertainty. Fuzzy disciplines are incorporated in the step of road localization. In this step, we first determine the color properties of road surface from the recovered road area by averaging the chromatic characteristics of the dominant pixels in the area.

Afterwards, a 2D fuzzy version, $\widetilde{B}$, of background image $B(t)$ is defined as follows. Let $\mu_B(x,y)$ be the membership function of $\widetilde{B}$, defined as

$$\mu_B(x,y) = \omega \frac{\sum_{S=r,g,b} |S_R(x,y) - S_{\bar{R}}(x,y)|}{\max\{D_i\}} + (1-\omega)\frac{d(x,y)}{\max\{d_i\}}, \quad (5)$$

where ω is a weighting factor; S_R and $S_{\bar{R}}$ are the respective chromatic characteristics of road images R and $\bar{R}$, in which $\bar{R} = B(t) - R$; and $d(x,y)$ is the distance from any point $p(x,y)$ to the nearest point of R. The denominators max$\{di\}$ and max$\{Di\}$ in the equation, where $D_i = |S_R - S_{\bar{R}}|_i$, are normalization terms. Finally, we associate the background pixels corresponding to the recovered road area R with the degree of membership of one. The above fuzzy membership function characterized by both chromatic characteristic and distance specifies the degree of a background pixel (x,y) belonging to the road region.

To locate the boundary of the road area, the next task is to select an adequate α-cut for the fuzzy membership function defined in Eq. (5). To this end, a process based on the ideas of shadowed sets previously introduced by Pedrycz (1998, 1999; Pedrycz & Vukovich, 2000) is employed.

To illustrate the shadowed sets of a fuzzy set, let X be the universal set on which a fuzzy set $\widetilde{A}$ is defined. Let μ_A be the membership function of $\widetilde{A}$. Given an α-cut, α, define a shadowed set function $\mathbb{A}_\alpha$ according to α as

$$\mathbb{A}_\alpha: \quad X \rightarrow \{0, 1, [0, 1]\}. \quad (6)$$

In other words, $\mathbb{A}_\alpha$ separates the elements in X into three subsets, S_0, S_1 and $S_{[0,1]}$, corresponding to $\mathbb{A}_\alpha$= 0, 1, [0, 1], respectively. In addition, S_0 is called the *core* of $\mathbb{A}_\alpha$ and $S_{[0,1]}$ is called the *shadow* of $\mathbb{A}_\alpha$. Given two shadows sets, $\mathbb{A}$ and $\mathbb{B}$, the basic operations (union, intersection, and complement) on them are shown in Table 1.

Table 1 Shadowed sets operations: (a) union, (b) intersection, and (c) complement, note that (a) and (b) are symmetric tables.

(a) union: $\mathbb{A} \cup \mathbb{B}$

$\mathbb{A}$ \ $\mathbb{B}$	0	1	[0,1]
0	0		Sym.
1	1	1	
[0,1]	[0,1]	1	[0,1]

(b) intersection: $\mathbb{A} \cap \mathbb{B}$

$\mathbb{A}$ \ $\mathbb{B}$	0	1	[0,1]
0	0		Sym.
1	0	1	

[0,1]	0	[0,1]	[0,1]

(c) complement: $\bar{\mathbb{A}}$

$\mathbb{A}$	0	1	[0,1]
$\bar{\mathbb{A}}$	1	0	[0,1]

The fundamental properties of shadowed sets operations are isomorphic with three-valued logic, i.e., Lukasiewicz logic. The interval, [0, 1], of shadowed sets is identical to the intermediate logical value, 1/2, of Lukasiewicz logic.The properties are illustrated as following equations, giving shadowed sets, $\mathbb{A}$, $\mathbb{B}$, and $\mathbb{C}$:

$\mathbb{A} \cup \mathbb{B} = \mathbb{B} \cup \mathbb{A}$, and $\mathbb{A} \cap \mathbb{B} = \mathbb{B} \cap \mathbb{A}$ (Commutativity)

$\mathbb{A} \cup (\mathbb{B} \cup \mathbb{C}) = (\mathbb{A} \cup \mathbb{B}) \cup \mathbb{C} = \mathbb{A} \cup \mathbb{B} \cup \mathbb{C}$

$\mathbb{A} \cap (\mathbb{B} \cap \mathbb{C}) = (\mathbb{A} \cap \mathbb{B}) \cap \mathbb{C} = \mathbb{A} \cap \mathbb{B} \cap \mathbb{C}$ (Associativity)

$\mathbb{A} \cup \mathbb{A} = \mathbb{A}$, and $\mathbb{A} \cap \mathbb{A} = \mathbb{A}$ (Idempotency)

$\mathbb{A} \cap (\mathbb{B} \cup \mathbb{C}) = (\mathbb{A} \cap \mathbb{B}) \cup (\mathbb{A} \cap \mathbb{C})$

$\mathbb{A} \cup (\mathbb{B} \cap \mathbb{C}) = (\mathbb{A} \cup \mathbb{B}) \cap (\mathbb{A} \cup \mathbb{C})$ (Associativity)

$\mathbb{A} \cup \varnothing = \mathbb{A}$, where $\varnothing$ is the empty set

$\mathbb{A} \cap \varnothing = \varnothing$

$\mathbb{A} \cup \mathbb{X} = \mathbb{X}$, where $\mathbb{X}$ is the universe set

$\mathbb{A} \cap \mathbb{X} = \mathbb{A}$ (Boundary Conditions)

$\bar{\bar{\mathbb{A}}} = \mathbb{A}$ (Involution)

In addition, a shadowed relation $\mathbb{R}$ is defined as following:

$$\mathbb{R}: (\mathbb{A} \times \mathbb{B})(x, y) \equiv \mathbb{A}(x) \wedge \mathbb{B}(y) \equiv \min(\mathbb{A}(x), \mathbb{B}(y)). \tag{7}$$

We now define three regions, referred to as the *rejected* Ω_1, *marginal* Ω_2, and *fully accepted* Ω_3 regions, respectively. Refer to Figure 2; mathematically,

$$\Omega_1: \int_{x:\mu(x)<\alpha} \mu_A(x)dx;$$

$$\Omega_2: \int_{x:\alpha\le\mu(x)\le 1-\alpha} dx;$$

$$\Omega_3: \int_{x:\mu(x)>1-\alpha} (1-\mu_A(x))dx. \tag{8}$$

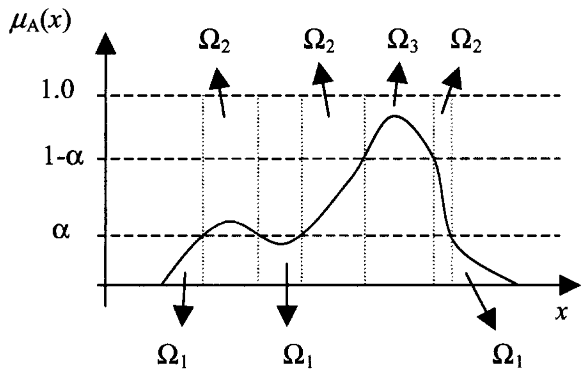


Figure 2. The illustration of balance of vagueness of a membership function $\mu_A(x)$

In order to determine an α-cut that best balances between the vagueness and clearness of the membership function μ_A, namely $\Omega_1 + \Omega_3 = \Omega_2$, define the balance equation $V(\alpha)$ to be

$$V(\alpha) = \left| \int_{x:\mu(x)<\alpha} \mu_A(x)dx + \int_{x:\mu(x)>1-\alpha} (1-\mu_A(x))dx - \int_{x:\alpha\le\mu(x)\le 1-\alpha} dx \right|. \quad (9)$$

When $V(\alpha) \to 0$, the vagueness and clearness of the membership function μ_A is balanced, i.e., the optimal α value will make $\arg\min_{\alpha} V(\alpha) = 0$, where $\alpha \in [0, 1/2]$.

For the 2-D case,

$$V(\alpha) = \left| \iint_{(x,y):\mu(x,y)<\alpha} \mu_A(x,y)dxdy + \iint_{(x,y):\mu(x,y)>1-\alpha} (1-\mu_A(x,y))dxdy - \int_{(x,y):\alpha\le\mu(x,y)\le 1-\alpha} dxdy \right|, \quad (10)$$

and for discrete cases, see Eq. (11) and (12), respectively.

$$V(\alpha) = \left| \sum_{\mu_A(x)<\alpha} \mu_A(x) + \sum_{\mu_A(x)>1-\alpha} (1-\mu_A(x)) - card\{x \mid \alpha \le \mu_A(x) \le 1-\alpha\} \right|, \quad (11)$$

$$V(\alpha) = \left| \sum_{\mu_A(x,y)<\alpha} \sum \mu_A(x,y) + \sum_{\mu_A(x,y)>1-\alpha} \sum (1-\mu_A(x,y)) - card\{(x,y) \mid \alpha \le \mu_A(x,y) \le 1-\alpha\} \right|. \quad (12)$$

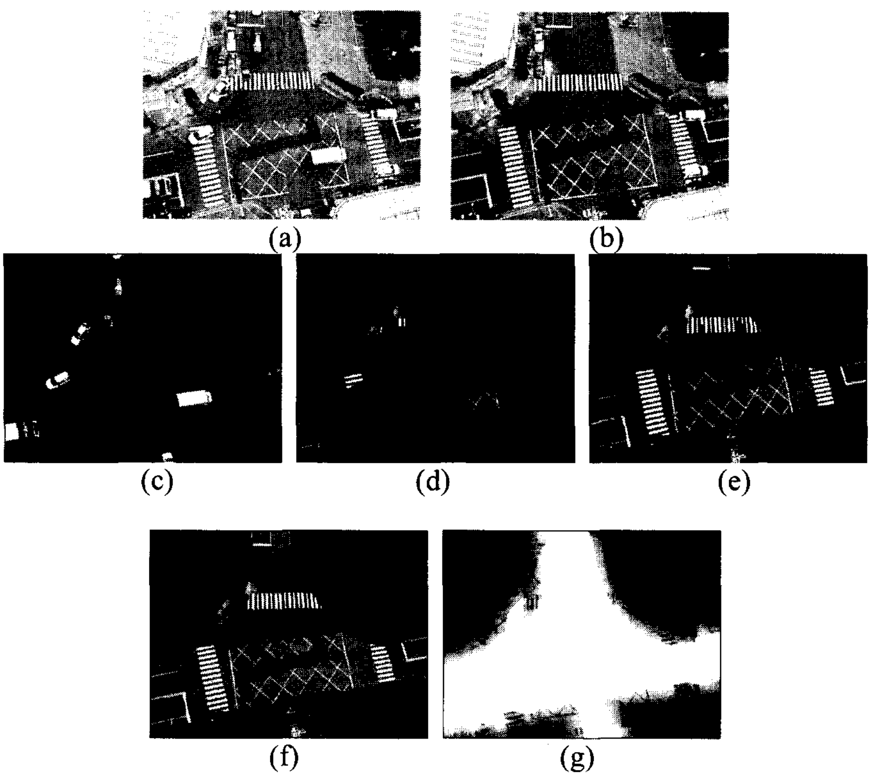
3. Experimental results

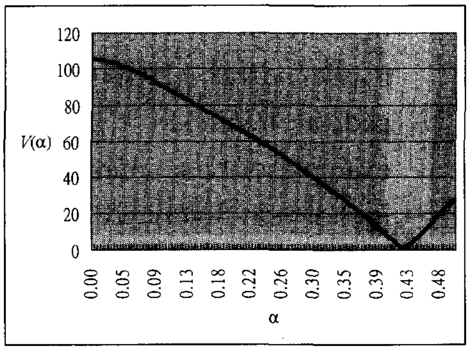
In our experiment, no particular specification for installation was imposed on the camcorder. The input image of the camcorder is first reduced to an RGB color image with a size of 320 by 240 pixels. Our program is written in the C language without any effort to optimize the speed and runs on a standard 2.4 GHz Pentium-based PC with 512 MB RAM. The computation for extracting the road area is very fast, taking only a few milliseconds on this PC;

however, the extraction method requires waiting for background generations.

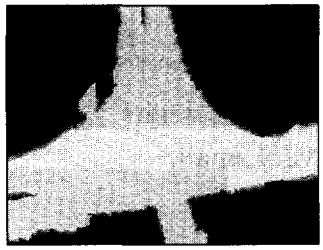
The input image of the first experiment is shown in Figure 3(a), for which a camcorder was installed on the top of a building nearby an intersection. Figure 3(b) shows a background image generated from a video sequence (about 200 images) of the scene displayed in Figure 3(a). Note that the vehicles parking on the road side will be considered as background objects if they are not moving during the processing period. Although our background generation process can perform quickly, it depends heavily on the traffic conditions, and it may take much more time to complete background image generation for traffic jams at rush hours. In addition, if a crowd of people is gathered on the sidewalk, the clutter will effect the procedure and may cause it to fail. We suggest not performing the initial steps in that case.

After generating the background image of the scene, the background image was used to extract foreground objects from the video sequence of the scene by image differencing. The foreground objects extracted from a video image are shown in Figure 3(c), where noise has been removed using morphological operations and connected component labeling. The background patches corresponding to the foreground objects are displayed in Figure 3(d). Figure 3(e) shows a road image of the scene, which was constructed by pasting the background patches collected from a sequence of 120 video images. The holes within the recovered road area are next filled by a morphological process shown in Figure 3(f).

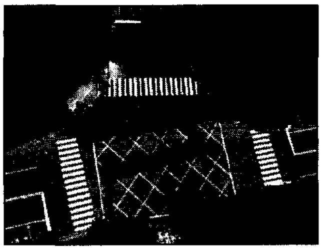




(h)

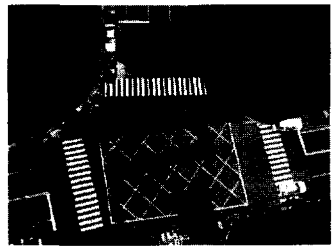


(i)



(j)

(k)



(l)

Figure 3. A detail experiment example, (a) the input video scene, (b) the generated background image, (c) extracted foreground objects, (d) the background areas corresponding to the foreground objects, (e) the major road component, (f) the hole filling result, (g) the fuzzy map, (h) minimizing $V(\alpha)$, (i) the defuzzified map, (j) the resultant road area, (k) the manually selected road area, (l) the manually selected road area background image.

Next, the boundary of the road region is determined using a fuzzy shadowed set technique. This technique first calculates the color properties (R_r = 148 for red, G_r = 160 for green, and B_r = 172 for blue in the scale of 256) of the road surface from the recovered road area. Based on the color properties of the road and the distance of pixels from the road, a fuzzy membership function is defined for the background image. Figure 3(g) shows the fuzzy version of the background image.

Afterwards, the α-cut (0.4258) that balances the credibility and vagueness of the fuzzy membership function is determined (see Figure 3(h)), which minimized the function $V(\alpha)$, i.e., $V(0.4258)$ = 0.1458. The fuzzy image, Figure 3(g), is then defuzzified by applying the determination of the α value (α = 0.3554) from the shadowed set operations. The result of the defuzzified image is also normalized to a 256 gray scale, as shown in Figure 3(i).

The output of detected road area is then obtained by combining the defuzzified image with the background information. In this example, the road area is detected and shown in Figure 3(j). For comparison, Figure 3(k) shows the road area manually selected, and Figure 3(l) is the manually selected road area background image. From Figures 3(j) and 3(l), it is clear that the major road area is correctly detected. For further applications such as vehicle tracking, accident detection or traffic flow monitoring, having the detected road area is very useful to eliminate unnecessary computation of the non-road area. In addition, the MSE (Mean Square Error) of comparing the estimated road area (Figure 3(j)) and the manually selected road area (Figure 3(l)) is 0.03443, which is very small.

Some additional experiment results are demonstrated in the following pictures. The color properties of road area for Figure 4(a) are obtained as red (R_r) = 88, green (G_r) = 100, and blue (B_r) = 88. In this experiment, the extracted road area is shown in Figure 4(b). The α value is obtained as 0.2930 (75 on a 256 gray scale), and the minimum V value is 0.1871. Another example of poor illumination on a cloudy day is shown in Figure 4(c). The color properties of road area for Figure 4(c) are obtained as red (R_r) = 60, green (G_r) = 72, and blue (B_r) = 72. In this experiment, the extracted road area is shown in Figure 4(d). The α value is obtained as 0.3359 (86 of 256 gray scales), and the minimum V value is 0.2153.

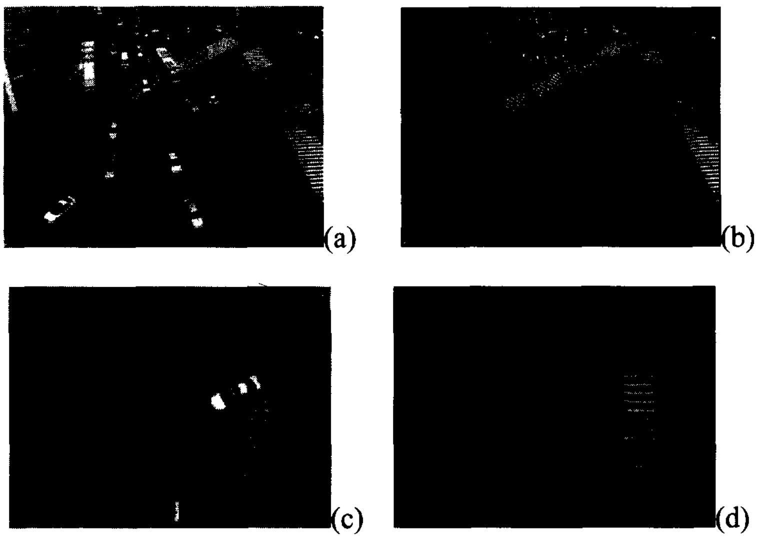


Figure 4. Experiment results, (a, c) are input scenes, (b, d) are road segmentation results, respectively.

The road segmentation process is often employed as a pre-process for other vision applications, such as tracking, counting or classification. As an initial procedure, it is often utilized in good weather conditions, mostly on sunny days. In contrast, our method is not limited by such conditions, and so can be applied in other environmental conditions such as nighttime and rain. Experiment results for road extraction on different environmental conditions are shown in Figure 5, where Figure 5 (a) is the input scene, Figure 5 (b) is the daytime results, Figure 5 (c) is the rainy daytime results, and Figure 5 (d) is the nighttime results.

For some extreme weather conditions, the proposed method can still provide good results; e. g., in Figure 6, the weather condition is a light rain with mist, together with the sun casting huge building shadows in the scene. Figure 6 (a) is the input scene, and Figure 6 (b) shows the background image, which clearly contains two huge building shadows. Figure 6 (c) is the results of extracted road area.

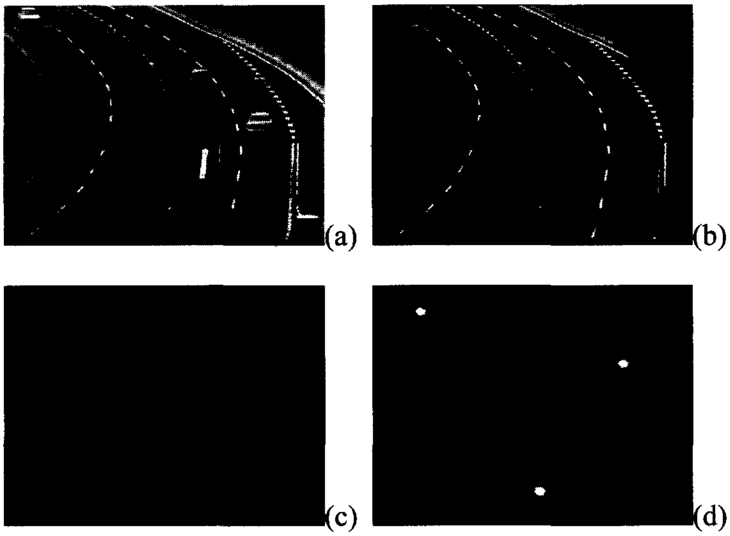


Figure 5. Experiment results for road extraction on different environmental conditions (a) is the input scene, (b) is the daytime results, (c) is the rainy daytime results, and (d) is the nighttime results.

4. Concluding remarks and future work

This paper proposes a road segmentation method consisting of four major steps: background image generation, foreground object extraction, background pasting, and road localization. To begin, the background image of a scene is generated. The generated background image is then used to fast extract foreground objects from each input video image. The background patches corresponding to the extracted foreground objects are pasted on an image, called the road image. A major component of the road region will gradually be constructed by repeating the previous steps. To obtain the full road region, hole filling and road localization are performed. Hole filling is accomplished by invoking a morphological process, and road localization is achieved using a fuzzy-shadowed set theoretical technique, which greatly simplifies the preceding steps.

Road segmentation is useful for a number of traffic applications, such as traffic surveillance, traffic flow measurement, traffic accident/incident detection, vehicle guidance, and driver assistance. Road segmentation provide useful information for precluding from further consideration irrelevant objects, events and activities so as to prevent their interference and unnecessary computations. The experimental results have revealed that the proposed method can effectively detect the road area without a priori information about both camera setup and image scale. In addition, the proposed method is not limited by environmental conditions such as nighttime or rain.

The proposed method is useful for traffic applications based on static images, although it is not suitable for dynamic images containing different backgrounds, e.g., driver assistance, vehicle guidance and automatic navigation. The research on extending fuzzy and shadowed sets methods to extract significant areas of dynamic images will be further topic of research.

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自動都市馬路區塊擷取

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摘　要

自動都市馬路區塊擷取於電腦視覺影像處理的應用上是非常重要的，舉例而言，交通流量偵測、交通監控、以及事件偵測等都需要這項技術為基礎。自動都市馬路區塊擷取可以提供影像中有效的路面區域，避免物件偵測程式浪費不需要的運算於非路面區域，並且可以減少錯誤偵測的發生。

本論文中所提出自動都市馬路區塊擷取方法使用了模糊與陰影集（fuzzy-shadowed sets）的方法來自動判斷路面的區域。本論文所提出的方法包括以下四個主要步驟：背景自動產生、前景物的偵測、背景黏貼法、路面定位。由實驗的結果中顯示，本論文所提出的方法在許多實際路面影像處理應用上都有良好的結果。

關鍵字：都市馬路區塊擷取、背景黏貼法、路面定位、模糊與陰影集