Generation and Adaptation of Transferable Roadway Model for Anticipative Road Following on Satellite-Roadway-Vehicle Network

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Abstract: By matching roadway images in an encountered scene with bird’s eye views, the scope of humans’ perception is expanded to a satellite-roadway-vehicle network. Based on the geometric consistency of the satellite images with as-is local terrain, in this paper, a computational mechanism is introduced for generation and adaptation of a roadway model transferable through the network. First, the chromatic complexity of the roadway area is represented as a palette of saliency colors via fractal sampling of the scene image. Next, the palette is adapted to the associated area in the bird’s eye view. Finally, the palette is transferred to the bird’s eye view for anticipatively following the roadway pattern. Experimental results demonstrate that the transferable model can be applied to the extension of the roadway pattern prior to physical access.

Key Words: transferable roadway model, satellite-roadway-vehicle network, image complexity analysis.

1. Introductory Remarks

As a consequence of co-evolution in uproarious illumination and reflection arising from friendly or undesirable neighbors, human’s vision seems to control the attention within the surroundings [1],[2] on the premise that sufficient information for imminent decision making is available as a ‘light speed’ transformation of ambient optic array [3]. Due to physical-geometric restriction of the perspective, the horizon of human’s inherent perception is not sufficient to span the range of reachability by current vehicle mechanisms. To operate computer-controlled vehicles going through natural scenes, hence, such a perceptual insufficiency should be restored by expanding the scope of decision making beyond the physical-geometric horizon. For this purpose, various types of machine intelligence have been developed and applied to the support of human’s decision making through global navigation [4] and situation understanding [5]. Noticing that the time for the awareness of the perception and decision making by neuronal steps amounts to one second [6], the machine intelligence should analyze the scene some hundreds meters beyond the physical perspectives.

Recent commoditization of the aerial images and/or remote sensing data makes it possible for the machine intelligence to capture the bird’s eye view including all possible destinations prior to physical access as illustrated in Fig. 1; in this schematics (a), as-is representation of the scenes to be encountered in the subsequent maneuvering processes are associated on the bird’s eye view of the expanded perspective; the bird’s eye view images archived by earth observation systems are retrieved as the latest representation of local terrain [7],[8] and linked with vehicle specific views via data relay systems as shown in (b). Due to the fluctuation of vehicles localization resulted from still ineluctable uncertainties in current version of the global positioning system (GPS) including the ionosphere instability [9], e.g., the association of the multi-viewpoint imagery requires simultaneous recognition of a complex pattern of the roadway observed via on-vehicles and on-satellites cameras. Adding to such a self-reference structure, the discrepancy between the times for capturing on-vehicle view and the perspective of the destination on arrival yields significant disparity between the distribution of impermanent objects in the bird’s eye view and the prediction of the scene. Hence, the integration of the global
navigation and the situation understanding under the perceptual insufficiency is still an open problem.

Noting geometric consistency of the satellite images with the local terrain, we consider a new problem called anticipative road following: the prediction of essential structure of the roadway scenes within the bird’s eye view beyond the horizon of the inherent perception. By using the on-vehicle camera under similar ambient light of the earth observation systems, we can upload the scene image into the bird’s eye view as an intrinsically equivalent visualization of the roadway pattern to be matched within a cut of practical satellite image. As a generic representation of such a roadway pattern for associating the multi-viewpoint imagery, in this paper, we introduce a class of fractal attractors to be confined a posteriori within the as-is distribution of the boundary objects. For decision makers going through the scene at a practical speed, the roadway pattern should be detected and chained as a connected region supporting a possible path to be planned in the scene. To this end, the fractal model is transferred and extended in the bird’s eye view prior to the physical access.

2. Chromatic Complexity Index

As the results of the evolution in the really existing world, human’s vision system is equipped with a sophisticated information processing mechanism for understanding the scenes filled with friendly or undesirable neighbors [10]. Through the iteration of selection pressure, the neighbors of the co-evolution process have developed various types of micro structures for the luminescence of their own optical messages. As intentional participants of the co-evolution process without the ‘intelligent designer’, human’s vision seems to be ‘preset’ to salient colors [11],[12]: scene specific spectral pattern discriminating ground area and/or object patterns from distractions and/or illusions in naturally complex scenes. Being supervenient on the optic array substantiated in the scene, the saliency information exhibits close correlation with various types of image features [13]. Such empirical facts imply that there should be a robust measure for indexing the chromatic complexity arising in natural scenes.

The perception of chromatic diversity is essentially mental processes; for most human observers only three primaries are required to match a test light [14]; noticing this, let the coloring of the reflected light be identified within the nonnegative subset of 3D Euclid space $R^3$:  

$$f_{\omega}^{RGB} \quad 0 \leq R_{\omega}, G_{\omega}, B_{\omega} \leq 1,$$

where $R_{\omega}, G_{\omega}, B_{\omega}$ are the intensities of three primaries at the pixel $\omega$ in the image plane $\Omega$. Define the chromatic information associated with the representation $f_{\omega}^{RGB}$ by  

$$\phi_{\omega} = \phi(f_{\omega}^{RGB}) = \frac{f_{\omega}^{RGB}}{f_{\omega}^{RGB}}.$$

By definition, the totality of the chromatic information is identified with the surface of the nonnegative unit sphere. Consider sufficiently consistent pair of the chromatic information $\phi_i$ and $\phi_j$ satisfying  

$$\langle \phi_i^T \phi_j \rangle \approx 1.$$

Since $\langle \phi_i^T \phi_j \rangle \sim \cos |\phi_i - \phi_j|$ by definition, and noting the following approximation

$$\cos |\phi_i - \phi_j| \sim \exp \left( -\frac{|\phi_i - \phi_j|^2}{2} \right),$$

is satisfied, we have the following Gaussian measure for evaluating the similarity of chromatic information

$$\left( \frac{\phi_i^T \phi_i}{2\pi} \right)^{\alpha} \sim g_\alpha(\phi_i, \phi_j) = \frac{1}{2\alpha \pi} \exp \left( -\frac{|\phi_i - \phi_j|^2}{2\alpha} \right),$$

with sensitivity parameter $\alpha > 0$. Following experimental studies using roadway scenes and various natural objects including human faces, dirt bank, paved road and so on, the sensitivity factor $\alpha$ should be adjusted to $1/10$–$1/100$. Thus, we have probabilistic evaluation for analyzing the chromatic diversity in naturally complex scenes.

Figures 2 and 3 demonstrate the significance of the chromatic information; in this case, 100 pixels are randomly sampled from the scene image (Fig. 2); all pixels in the scene image are replaced by a sample which is nearest in the sense of the Gaussian evaluation (1); by this chromatic matting, we have a palette for reducing the complexity of the scene image (Fig. 3). This implies that we can index the chromatic complexity arising in natural scenes in terms of the measure (1).

In this experiment, the random samples were generated via the self-similarity process illustrated in Fig. 4: the image plane $\Omega$ with four vertexes are reduced into four copies via a system of contraction mappings $\mu_1$, ..., $\mu_4$; the rectangle $\Omega$ is generated as the collage of the reduced rectangles $\{\mu_i(\Omega)\}$. This reduction-and-collage process can be simulated by random application of the mapping set $\{\mu_i\}$ to implement an efficient sampling mechanism of a fixed rectangle region. The validity of the palette in such an impression regeneration implies that the fractal attractors associated with the self-similarity process can be
utilized as a computational basis of naturally complex objects in practical scenes.

3. Adaptation of Chromatic Complexity

In the previous section, we have a compact palette through the fractal sampling associated with the self-similarity process regenerating the entire image plane asymptotically. By invoking fractal collage theorem [15], we can design the self-similarity process controlled by a set of contraction mappings from the image plane to itself. On the other hand, we can approximate any roadway patterns in the satellite images in terms of a chain of the rectangles resulted from the imaging process shown in Fig. 4. Noticing such a computational equivalence of the road patterns captured from the viewpoints of on-vehicle and on-satellite cameras, in this section, we consider the following matching problem: how to identify the image of the roadway pattern in the multi-viewpoint images under the significant discrepancy of illumination and optical conditions.

For the first step, we design a self-similarity process to cover the roadway area in a view of the scene image captured via the on-vehicle camera. Suppose that the scene image is represented by the distribution \( f_{\omega}^{RGB} \), \( \omega \in \Omega \). By applying the self-similarity process, we have associated fractal attractor \( \Xi \) spanning over a significant part of the roadway area. By sampling pixels on the attractor, we can specify the chromatic diversity of the roadway area in terms of the following palette

\[
\mathcal{s} = \left\{ f_{\xi}^{RGB} \in R_1^3 \mid \xi \in \Xi \right\}. \tag{2}
\]

Let the diversity of the palette \( \mathcal{s} \) be indexed by

\[
\mathcal{R}_s = \frac{1}{2\pi \alpha} \exp \left[ -\frac{c_2^2}{2\alpha} \right], \tag{3}
\]

where \( \mathcal{R}_s \) denotes the size of the palette \( \mathcal{s} \) and \( \phi_1 \) designates the chromatic information associated with the distribution \( f^{RGB} \) at \( \omega = \xi_1 \) with \( \xi_1 \in \Xi \). Then we have the following matching rule for associating the pixel \( \omega^* \) of the value \( f^{RGB} \) with the palette \( \mathcal{s} \):

\[
g_s(\omega^*) > \mathcal{R}_s \Rightarrow f^{RGB} \in \mathcal{s}, \tag{4}
\]

where \( g_s(\omega^*) = \max_{\phi_1 \in \phi(\mathcal{s})} g_s(\phi_1) \), with \( \phi(\mathcal{s}) = \left\{ \phi(f^{RGB}) \mid f^{RGB} \in \mathcal{s} \right\} \). The matching criterion (4) is used to refine the palette \( \mathcal{s} \); if \( f^{RGB} \) and \( f_j^{RGB} \) satisfy the criterion, \( f_j^{RGB} \) or \( f_j^{RGB} \) is eliminated from the palette \( \mathcal{s} \). By this process, the size of palette can be reduced to 1/30-1/50 of sample size \( \| \Xi \| \).

Next, let \( \hat{\Omega} \) be another image plane in which current location of the vehicle is estimated at a pixel \( \hat{\omega} \in \hat{\Omega} \) within a pre-sampled GPS residual. Suppose that another set of the distribution \( \left\{ f_{\omega}^{RGB} \mid \omega \in \hat{\Omega} \right\} \) is sampled from a small area around the estimate \( \omega \). Assume that the GPS residual is sufficiently small so that the support of the distribution \( f_{\omega}^{RGB} \) is not disjoint with a pattern \( \Xi \subset \hat{\Omega} \); the bird’s eye view of the roadway pattern \( \Xi \) captured by the on-vehicle camera. After the redundancy reduction process described by (3) and (4), the samples \( f_{\omega}^{RGB} \) are reduced to specify a new palette \( \hat{\mathcal{s}} \) in the satellite image to be matched with \( \mathcal{s} \). The palette \( \hat{\mathcal{s}} \) generally suffered from considerable spectrum shift due to the discrepancy of the ambient light surrounding on-vehicle and on-satellite cameras. Adding to it, due to the fluctuation of the GPS residual, it is not easy to restrict sampling points of the palette \( \mathcal{s} \) within the roadway area to be detected. To restore the spectrum shift, the palette \( \mathcal{s} \) is statistically adapted to the satellite image as follows:

\[
\hat{\mathcal{s}} = \left\{ f^{RGB}_{\hat{\omega}} + \delta\hat{\omega} \in R_1^3 \mid f^{RGB}_{\hat{\omega}} \in \mathcal{s} \right\}, \quad \delta\hat{\omega} = \hat{\mathcal{s}} - \mathcal{s}, \tag{5a}
\]

where \( \hat{\mathcal{s}} \) stands for the shifted version of the palette and

\[
\hat{\mathcal{s}} = \frac{1}{\| \hat{s} \|} \sum_{f^{RGB}_{\hat{\omega}}} f^{RGB}_{\hat{\omega}}, \quad \hat{\mathcal{s}} = \frac{1}{\| \hat{s} \|} \sum_{f^{RGB}_{\hat{\omega}}} f^{RGB}_{\hat{\omega}}. \tag{5b}
\]

The final step is the estimation of the palette \( \hat{\mathcal{s}} \) associated with the roadway pattern to be detected in the satellite image. For this purpose, the chromatic information sampled from the exterior of the roadway pattern is classified and eliminated via the following topological test:

\[
\hat{\mathcal{s}} = \left\{ f^{RGB}_{\hat{\omega}} \in \hat{\mathcal{s}} \mid \exists f^{RGB}_{\hat{\omega}} \in \hat{\mathcal{s}} : \mathcal{R}_s \geq \max \left\{ g_s(\phi(\mathcal{s})) \mid \mathcal{R}_s \right\} \right\}. \tag{6}
\]

The schematic of the adaptation process is illustrated in Fig. 5. In (a), the complexity of two palettes, \( \mathcal{s} \) and \( \hat{\mathcal{s}} \) collected from on-vehicle and on-satellite camera, respectively, are represented as two clusters of chromatic information endowed with statistical moments. The origin palette \( \mathcal{s} \) is shifted along the vector \( \delta\hat{\omega} \) towards the target \( \hat{\mathcal{s}} \) to apply the rule (6); the shifted samples \( \hat{\phi}_1 \) and \( \hat{\phi}_2 \) are matched to select mutually nearest samples \( \hat{\phi}_1 \) and \( \hat{\phi}_2 \) to \( \delta\hat{\omega} \) as equivalent estimate \( \hat{\phi}_1 \) \( \hat{\phi}_2 \) and non-equivalent estimate \( \hat{\phi}_1 \) \( \hat{\phi}_2 \), respectively; on the other hand, asymmetrically nearest pairs \( \hat{\phi}_1 \), \( \hat{\phi}_2 \) and \( \hat{\phi}_1 \), \( \hat{\phi}_2 \) are classified as non-transferable information in the generation of the estimate \( \hat{\mathcal{s}} \). By invoking the criterion \( \mathcal{R}_s \) we can induce an equivalence relation to eliminate non-nearest chromatic information from the shifted palette \( \hat{\mathcal{s}} \). Thus, the palette \( \mathcal{s} \) generated in the scene image can be simplified and transferred into the satellite image without explicit description of the roadway pattern \( \hat{\Xi} \).

4. Anticipative Road Following

The adaptation process formulated by (2), (4) and (6) yields a transferable version of generic roadway model \( \hat{\mathcal{s}} \) with the consistency index \( \mathcal{R}_s \) \( \| \mathcal{s} \| \). By using this \( (\hat{\mathcal{s}}, g_s, \mathcal{R}_s, \| \mathcal{s} \|) \) model, the \( f^{RGB}_{\hat{\omega}} \) \( f^{RGB}_{\hat{\omega}} \) distributions are precisely matched to associate the roadway pattern on-vehicle and on-satellite camera images. Within the schematics of the satellite-roadway-vehicle
integration illustrated in Fig. 1, satellite images of sufficiently small scales are used for indicating vehicles and their specific destinations at a glance. In such a situation, we can exploit conventional Hough voting scheme with respect to the consistency index $g_\alpha [\cdot \mid \hat{s}]$ for the simultaneous identification of the roadway pattern and vehicles location as a short vector and its origin, respectively. As the result, we have vehicle specific representations of local roadway patterns in terms of the matched origin, allocated to the updated origin $\hat{\omega}_t$.

The connectedness of the local roadway pattern is evaluated along two-leveled chaining of the vector $\hat{v}_t$. The schematics is illustrated in Fig. 6 where a set of connected vectors $\{\hat{b}_i\}$ are detected and chained to specify the local roadway pattern $\hat{\omega}_t$. First, the connectedness of the vector $\hat{b}_i$ is indexed in terms of the following measure as well:

$$g_\alpha (\hat{b}_i \mid \hat{s}) = \sum_{\hat{\omega}_s \in b_i} g_\alpha \left( \phi \left( f_{\text{RGB}}^{\hat{\omega}_s} \right) \mid \phi \left( f_{\text{RGB}}^{\hat{s}} \right) \right) 	imes g_\alpha \left( \phi \left( f_{\text{RGB}}^{\hat{\omega}_s} \right) \mid \hat{s} \right), \quad (7a)$$

where $\hat{\omega}_s$ is selected in the sequence of pixels sampling the vector $\hat{b}_i$ with distance $d_{\text{歐}}$. By using the measure $g_\alpha (\hat{b}_i \mid \hat{s})$, we can evaluate the a priori consistency of the one-step prediction of the roadway pattern to the destination

$$\hat{\omega}_{t+dt} = \hat{\omega}_t + \hat{b}_i, \quad (7b)$$

in the satellite image. The iteration of the consistency-based extension (7) yields a local roadway pattern $\hat{\omega}_t$ consisting of a sequence of the roadway segments $\hat{b}_1, \hat{b}_{1+dt}, \hat{b}_{1+2dt}, \ldots$ with associated stopovers $\hat{\omega}_{t+dt}, \hat{\omega}_{t+2dt}, \ldots$ to be chained beyond the perspective of the on-vehicle vision. The consistency of the extended segments is indexed in terms of the measure $g_\alpha (\hat{\omega}_t \mid \hat{s})$ given by

$$g_\alpha (\hat{\omega}_t \mid \hat{s}) = \min_f g_\alpha (\hat{b}_i \mid \hat{s}). \quad (8)$$

5. Experiments

Let the scene image be captured as shown in Fig. 2 where the on-vehicle camera is directed to the depth of the roadway area. In this figure, the brightness distribution was binarized along the horizontal scan lines to detect left- and right- white lines confining the object free space as illustrated in Fig. 7. By assigning the vertices of the space to the estimate of the fixed points $\hat{\Omega}' = \{\hat{\omega}_{\Omega}'\}$ to control the self-similarity process as shown in this figure, we have a design of the roadway model. The fractal model was applied to the sampling of chromatic information in the scene image as indicated in Fig. 8; via 10,000 times iteration of Monte Carlo simulation of the self-similarity process [16], 9,122 unique pixels were selected as the attractor points in the triangles confined by the vertices $\{\hat{\omega}_{\Omega}'\}$ from these points, first 640 pixels were used to evaluate the diversity factor $R_\alpha$. As the result, in this case, the geometric-chromatic redundancy of the fractal sampling were reduced to specify a on-vehicle palette $s$ consisting of 228 representatives of chromatic information. To verify the consistency of the reduction process (4), the palette was matched with the $f_\alpha^{\text{RGB}}$-distribution in the scene image to yield the ‘matted’ image as shown in Fig. 9. This figure demonstrates that only 2% of color samples are sufficient to support the chromatic complexity of the roadway area. Furthermore, the reduced palette is consistent with the entire

![Fig. 5 Schematics of chromatic complexity adaptation.](image)

![Fig. 6 Schematics of anticipative road following.](image)

![Fig. 7 Lane image.](image)
image of the roadway area out of the fractal attractor. This implies that the resulted palette can be applied to the detection of the roadway area beyond the physical-geometric restriction of the perspective.

To demonstrate the robustness of the fractal model, the on-vehicle palette \( s \) was adapted to a aerial photograph. The results of the adaptation process are indicated in Figs. 10–12 with Table 1. In Fig. 10, the viewpoint of the scene (Fig. 2) is located in a circle specified by using the GPS. In this figure, the radius of the circle indicates the uncertainty of the GPS based on the ionosphere instability model [9]. From this circle, another set of chromatic information were sampled as the reference to the on-vehicle palette \( s \). The performance of the adaptation process is summarized in Table 1; from the aerial photograph, 155 samples of unique chromatic information were selected to specify the bird’s eye view version of the palette \( \hat{s} \) with mean value \( \bar{z} = (0.55873 \ 0.61595 \ 0.55536) \) and the diversity factor \( 2\pi\alpha R_s = 0.9922 \); by shifting the mean value \( \bar{z} \) towards \( \bar{s} \), we have the estimate \( \hat{s} \), to be transferred to the bird’s eye view. As shown in this table, the refinement process (6) reduces the size of the estimate to 6.6% of the initial palette \( s \) without any degradation of the matching accuracy. Through the adaptation procedure (6), the size \( ||s|| \) and the granularity \( R_s \) are maintained in the transferable palette \( \hat{s} \). In Fig. 11, the chromatic complexity of the palette \( \hat{s} \) is visualized with the comparison of \( s \) and \( \hat{s} \). In this figure, the sample colors in the palettes \( s \) and \( \hat{s} \) are randomly distributed in the background rectangle and right circle, respectively. The implication of the selective adaptation process (5)–(6) is displayed in the left circle in which color samples in \( \hat{s} \) are randomly distributed. As shown in this figure, the chromatic complexity of the scene image is refined and transferred as a consistent information of the not-yet-identified roadway pattern in the bird’s eye image. The adapted palette \( \hat{s} \) was applied to the detection of the roadway pattern as shown in Fig. 12 where a segment through the circle was identified via Hough voting scheme with matching criterion (4). In this figure, the center of the sampling circle is shifted to the origin of the segment \( \hat{\omega}_t \); the possible directions of the vector \( \hat{v}_t \), designated by \( \hat{\theta}_t \), is displayed as a line crossing the origin.

The detected segment \( \hat{\theta}_t \) was extended through the iteration...
Fig. 13 Local segmentation to be chained.

Fig. 14 Anticipative road following in satellite image.

Fig. 15 Chromatic consistency of extended segments.

Fig. 16 Fractal sampling of scene [17].

Fig. 17 Locating result of the scene by GPS.

Table 2 Adaptation of palette to Fig. 17.

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Figures 16–19 illustrate the results of another experiment. By applying the Laplacian-Gaussian clustering to the noise pattern distributed in the scene image [17], we have another version of fractal model without any a priori knowledge of the lane as shown in Fig. 16; in this case, designed fractal attractor is spilled over into the reverse lane; thus, resulted palette \( \hat{s} \) should include the color of the center line to be eliminated from the open space model. Such a corrupted palette \( \hat{s} \) was refined and adapted to the satellite image indicated in Fig. 17 where the scene is associated within the circle of the GPS residual to extract another version of on-satellite palette \( \hat{s} \).

The results of the segmentation-extension process are indicated in Figs. 18 and 19 with Table 2; the fractal model is transferable to the satellite image as well; the matched segments can be extended along the roadway pattern as a connected chains towards a possible destination successfully.

The performance of the generation and adaptation process for the transferable roadway model is summarized in Table 3 where the palettes based on the fractal design and the lane detection are compared; in these experiments, first, 640 pixels were sampled via Monte Carlo simulation of fractal attractors [16] in the triangles confined by the vertices \( \{ \hat{\omega}_i \} \); next, the samples were
refined and adapted to the bird’s eye views of the scene. By applying the fractal model, the support of the chromatic complexity consisting of of 91,840 and 53,983 pixels, respectively, were reduced to the subsets consisting of 0.7–1.2% representatives; via the adaptation process (6), the palette $s$ was generated based on $1/2–1/3$ of the representatives; for extending the segment, the palette $s$ was refined to yield the estimate $\hat{s}$ in which only $1/15–1/30$ palette elements were maintained. As the result, the fractal representation of roadway patterns provides compact transferable model consisting of at most 15 samples of saliency colors.

### 6. Discussions

Experimental results stated in the previous section demonstrate that the on-vehicle palette $s$ can be efficiently extracted via the fractal sampling and transferred for the anticipative road following in the bird’s eye views. As demonstrated in Figs. 10 and 17, the palette $s$ can be transferred to the bird’s eye views spanning considerable spectrum shift. Adding to such a robustness, Figs. 15 and 19 show that the transferred palette is sufficiently sensitive to detect the limit of the extension process in possible chromatic variation along the roadway pattern. Such a computational integrity is useful to implement a self-articulation mechanism; restarting $s \rightarrow \hat{s}$ process at detected halt point of the anticipative following scheme described in Fig. 6. Supported by the empirical knowledge on the uniform distribution of chromatic randomness combined with the fractal modeling, the palette can be transferred to the bird’s eye view to reach a destination point prior to physical access. Via such anticipative road following, the roadway pattern beyond the horizon of the on-vehicle vision is represented in terms of a chain of the vectors $\hat{b}_t$. Thus, the on-vehicle vision can exploit structural prediction for analyzing not-yet-observed scenes. For instance, by computing the vanishing point in terms of the prediction $\left(\hat{w}_t, \hat{b}_t\right)$ at future time $t$, the fractal modeling process shown in Figs. 7 and 16 can be preset, in turn.

The reliability of the anticipative road following can be evaluated by the transition of the measure $g_{\hat{s}}(\hat{b}_t | \hat{s})$ as indicated in Figs. 15 and 19. As shown in these figures, the measure is sufficiently sensitive to chromatic discrepancy due to possible distributions of moving objects. Simultaneously, the rapid restoration of the evaluation means the robustness of the palette $\hat{s}$ to be matched spanning over the local discrepancies. Such robustness of the palette is supported by the transfer scheme (6) where the saliency colors are extracted via in situ sampling of a visible cut of the scene in contrast with the conventional method based on a fixed primaries system [13].

Since the adaptation $s \rightarrow \hat{s}$ implies the existence of reverse process $s \leftarrow \hat{s}$, it is hopeful to exploit the transferable model as an over-the-horizon prediction of the scene to be encountered. To download the palette $\hat{s}$ to practical roadway scenes, the sampling region should be strictly confined as shown in Fig. 7 to concentrate the palette $s$ on the roadway specific samples as shown in Fig. 8. By this restriction, we can exploit the non-empty estimate $\hat{s} \leftarrow \hat{s}$, if exists, as a representation of a sub-region of the roadway area. The expansion of the subregion to the estimate of the maneuverable area within the context of the road following problem is left to future investigations.

### 7. Concluding Remarks

Probabilistic indexing of the chromatic complexity was demonstrated to provide effective information for designing roadway model transferable through a satellite-roadway-vehicle network. Via fractal sampling of the scene images, the chromatic complexity of the roadway area can be represented by a palette consisting of at most 15 samples of saliency colors. By precisely matching the palette with the bird’s eye image, we can extend the roadway pattern some hundreds meters prior to physical access. The author intends to develop stochastic control of maneuvering process in cooperation with the anticipative road following scheme as a next step.

### References


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He received his M.S. and Ph.D. degrees from the Kyoto Institute of Technology and Kyoto University, Japan, in 1973, and 1991, respectively. From 1973 to 1994, he was with the Central Research Laboratory and Mechanical Engineering Research Laboratory of Hitachi Ltd. Since 1994, he is with the Osaka Institute of Technology. His research interests include stochastic and computational aspects in modeling and implementation of cooperative information systems. He is a member of ISCIE, JSME, and IEEE.