Saliency-Based Notabilia Re-Detection via *As-is* Primary Transfer

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November 22, 2015

**Abstract:** A robust color matching scheme is presented for future re-detection of landmark sign/design annotated by probe vehicles. By indexing inherent susceptivity to chromatic diversity in terms of the *as-is* primary, the re-detection process nondeterministically restore the saliency patterns spanning significant discrepancy of ambient light. Annotated and re-detected saliency patterns maintain various types of *notabilia* to be identified for facilitating over-the-horizon cooperation.

**Keywords:** Pattern Re-Detection; Saliency-based Approach; Geographics Annotation; Over-The-Horizon Cooperation

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1 Introductory Remarks

Design and instantiation of intentional maneuvering processes within first visit scenes are essential tasks in daily life and robot operation as well. However, it is not easy even for human’s inherent perception to get a distant view of everyday scenes confined by complex distribution of boundary objects. Despite such a physical-geometric restriction, we can deploy a multitude of ‘probe’ vehicles to jointly facilitate over-the-horizon cooperation of maneuvering processes. To implement the over-the-horizon cooperation, the information gathered by the probe vehicles should be integrated through robotic communication [12] as illustrated in Fig. 1 where map builders and on-vehicle visions are networked to augment the annotations of local geographics in terms of the landmarks and scene images; such distributed annotations are interactively associated for path planning and landmark localization within user specific maneuvering contexts as well as anticipative programming of vehicle control systems [17]. In reference to the landmark annotation by such robotic probes, a set of route graphs are generated on the bird’s eye view; the route graph is matched with GPS tracks of probe vehicles to adapt the symbolic plan to physical-geometric descriptions of the local geographics. By broad-catching the landmark annotations through the state-of-the-art space systems [11], we have an augmented scope of perception as computational support of the essential tasks including linguistic route instruction [2] and geometric travel planning [4].

At the first visit, the on-vehicle vision systems are required to match the probed images within natural scenes including unexpected distribution of background objects. To facilitate such an adaptation process, hence, probe vision should generate transferable representation of notabilia: signals, sign boards and pedestrians, e.g., to be encountered in visitor’s view. In many practical situations, however, it is not easy to specify ‘what-to-be-observed’ in complex scenes prior to the completion of the missioned program. Despite such a computational difficulty, it is well known that humans have developed a not-yet-explicated capability to focus inherent vision to saliency patterns [8] conveying signs and/or design of cordial and/or hostile neighbors [16]. Following empirical knowledge of neural sensitivity to fractal patterns [6] combined with recent advancements in emotional perception [7], let the following working hypothesis be set up: the saliency distribution should be self-organized within notabilia patterns to induce the understanding of the scenes. On the working hypothesis, in this paper, we reformulate the problem of scene analysis within the augmented scope of perception; the problem is to identify the control parameter to concentrate computation resources to the notabilia patterns within the observed- and possible perspectives of robotic probes and future visitors, respectively. Based on preliminary results on chromatic diversity analysis, a robust control parameter, called as-is primary, is identified in section 3; following experimental studies, the effectiveness and robustness of the as-is primary are demonstrated in 4 and 5, respectively; by clarifying the complexity reduction via the notabilia pattern detector in section 6, finally, the implications and limitation of the as-is primary transfer are discussed in the context of over-the-horizon cooperation.

2 Locally Gaussian Color Space

Noticing that the coloring of reflected light should be matched through essentially mental process [5], in this section, some preliminary results for saliency distribution analysis are summarized. Following the framework of RGB-primary based color matching test, let the information conveyed by chromatic diversity be represented within the nonnegative subset of 3D Euclid space:

\[ f_{\omega}^{RGB} = \begin{bmatrix} R_{\omega} & G_{\omega} & B_{\omega} \end{bmatrix}^T, \quad 0 \leq R_{\omega}, G_{\omega}, B_{\omega} \leq 1, \]
where \((\cdot)_{\omega}\), \((\cdot) \in \text{RGB}\) are the intensities of three primaries at the pixel \(\omega\) in the image plane \(\Omega\). To precisely evaluate chromatic diversity in randomly varying ambient light, define
\[
\phi_{\omega} = \left[\phi_{R\omega}, \phi_{G\omega}, \phi_{B\omega}\right]^T, \quad \phi^{(i)} = \frac{(\cdot)_{f_{\text{RGB}}^{i}}}{|f_{\text{RGB}}^{i}|},
\]
and suppose that the shift of the chromatic information \(\phi_{\omega}\) is detectable in terms of the following measure induced in the positive part of a unit sphere:
\[
g_{\alpha}(\phi|\phi_{\omega}) = \frac{1}{2\pi\alpha} \exp\left[-\frac{|\phi - \phi_{\omega}|^2}{2\alpha}\right]. \tag{1}
\]
For sufficiently small deviation \(|\phi - \phi_{\omega}|\), \(g_{\alpha}(\phi|\phi_{\omega})\) approximates the Gaussian distribution on tangential space at \(\phi_{\omega}\). By applying such local indexing to a set of color samples \(s = \{\phi_i = \phi(f_{\text{RGB}}^{i}), i = 1, 2, \ldots, n\}\) collected in a scene image, we have the following equivalence criterion:
\[
R_{\alpha} = \frac{1}{2\pi\alpha} \exp\left[-\frac{\sigma_{\phi\phi}^2}{2\alpha}\right], \tag{2}
\]
\[
\sigma_{\phi\phi}^2 = \frac{1}{n(n-1)} \sum_{1 \leq i,j \leq n, i \neq j} |\phi_i - \phi_j|^2.
\]
By selecting representatives with respect to the \(R_{\alpha}\)-equivalence, we have a ‘palette’
\[
s^* = \left\{\phi^*_j = \phi(f_{\text{RGB}}^{j}) \mid \omega^*_j \in \Omega\right\},
\]
to regenerate the chromatic diversity. An example of the palette generation process is illustrated in Fig. 2; 995-samples of \(\phi(f_{\text{RGB}}^{i})\)-information are collected in a scene image as shown in the main window (a); via the \(R_{\alpha}\)-equivalence test, a small palette \(s^*\) with size \(|s^*| = 175\) is generated. In the (b)- and (c) subwindows, the diversity of the samples \(s\) and resulted representatives \(s^*\) are visualized within the planar color space \(\Gamma\) on which the information \(\phi_{\omega} = \phi(f_{\text{RGB}}^{\omega})\) is mapped via the following projection:
\[
\Gamma \ni \gamma = e_{\text{RGB}}^{\phi_{\omega}}, \quad e_{\text{RGB}}^{\phi} = \begin{bmatrix} e^R & e^G & e^B \end{bmatrix}, \quad e^{(i)} = \begin{bmatrix} \cos \theta_i \sin \theta_i \end{bmatrix}^T, \tag{3}
\]
where \(\theta_R = \pi/2, \theta_{G(B)} = \theta_R + (-)2\pi/3\). Figure 3 demonstrates an implication of palette generation; in this figure, the nearest representative is selected in (c) to substitute for each pixel color to yield a ‘matted’ image as displayed in (a). This figure implies that we can utilize the palette \(s^*\) to restore the chromatic diversity spanning various notabilia patterns. Thus, the palette \(s^*\) yields a statistical representation of all possible spectral variations within the locally Gaussian color space.

Despite of the regenerativity, the palette is essentially supervenient on the spectral shift of ambient light; to transfer the notabilia patterns, the palette \(s^*\) should be pre-selected from a possible version of future scenes. From the viewpoint of neuronal computation systems, the color matching process is substantiated by stochastic capturing mechanism of a set of photopigments [3]. To clarify the computational structure of robust color recognition by inherent vision, consider probabilistic indexing of such a
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Figure 3: Representative-based Complexity Reduction: \( f_{\omega}^{\text{RGB}} \mapsto f_{\omega}^{\text{RGB}} \)

![Image](image1.png)

Figure 4: RGB-Based Saliency Distribution: \( \psi_{\omega}^{\text{RGB}} \)

![Image](image2.png)

distributed neuronal process. Since \( \sum_{c \in \{ \text{RGB} \}} (\phi_{\omega}^{c})^2 = 1 \), we have a ‘square root’ representation of of the neuronal capturing probability in terms of the normalized vector \( \phi_{\omega} \). This implies that the probability for capturing photopigments under the condition of the trichromatic primary matching is evaluated by

\[
p(\phi_{\omega}|(\cdot)) = (\phi_{\omega}^{c})^2, \quad c \in \text{RGB}.
\]  

Thus, the \textit{a posteriori} probability for trichromatic photopigments selection is evaluated by

\[
p(c|\phi_{\omega}) = \frac{p(\phi_{\omega}|c) \cdot p(c)}{\sum_{c \in \text{RGB}} p(\phi_{\omega}|c) \cdot p(c)},
\]

with \textit{a priori} information \( p(c) = 1/3 \). Following Kolmogorov [14], let the chromatic preference be indexed in terms of neuronal computation cost, i.e.,

\[
\mathcal{H}_{\omega} = - \sum_{c \in \text{RGB}} p(c|\phi_{\omega}) \log p(c|\phi_{\omega}).
\]

Figure 4 illustrates the significance of the entropy-based indexing where the following pixel-wise filter is applied to enhance the saliency patterns to be detected in the scene image (Fig. 2):

\[
\psi_{\omega} = 1 - \exp \left[ -\frac{1}{2} \left( \frac{\log ||\text{RGB}|| - \mathcal{H}_{\omega}}{\log ||\text{RGB}|| - \mathcal{H}_{m}} \right)^2 \right],
\]

\[
\mathcal{H}_{m} = \frac{1}{||\Omega||} \int_{\Omega} \mathcal{H}_{\omega} d\omega,
\]

where the loss by ‘busy time’ of neuronal capturing mechanism is estimated in terms of the Shannon entropy spanning \( 0 \leq \mathcal{H}_{\omega} \leq \log ||\text{RGB}|| \). By applying the chromatic preference indexing to entire the image plane, we can detect the distribution of ‘easy to compute’ representation \( \psi_{\omega} f_{\omega}^{\text{RGB}} \) as visual saliency. As shown in Fig. 4, the resulted saliency patterns well emphasize a set of man-readable objects successfully. This implies that the \( \psi_{\omega} \) transformation induces a probabilistic preference indexing within the locally Gaussian color space supporting all possible chromatic variations under the control of RGB-primary.
3 Chromatic Complexity Generator

Despite significant information compression, we can restore the impression of notabilia patterns as indicated in Figs. 3 and 4. However, due to the sensitivity of the palette to ‘all visibles’ as demonstrated in Fig. 3, it is not easy to re-apply the representatives to visitor’s view spanning significant discrepancy of ambient light. In addition, the comparison of these figures implies that the spectral shift of ambient light may yields serious oversights in the RGB-based saliency imaging. To transfer the essential information conveyed by the observables s, the RGB-primary should be adapted to the as-is representation of the chromatic diversity. Noticing the robustness of the chromatic complexity within random variation of photographing conditions, consider the identification of s-generator within the framework of self-similarity imaging processes [9].

Mathematically, the chromatic diversity conveyed by the samples s is identified with the aggregation of Dirac’s delta measure distributed on $\Gamma_s = \left\{ \gamma(\omega) : \omega \in s \right\}$. Noting this, consider stochastic-computational model for simulating the robustness of the inherent saliency preference; the focus to the notabilia patterns should be controlled through the primary-based neuronal computation; the notabilia color should be selected within complex distribution $\Gamma_s$. To implement such a complexity generation mechanism, let the distribution $\Gamma_s$ be identified with a degenerated version of fractal attractor $\Xi_s$; without serious loss of generality, suppose that the attractor is generated via the iterated function system [1]. This implies that the computational structure of $\Xi_s$ can be restored through self-similarity analysis of the following measure:

$$\chi_s = \sum_{\phi \in s} \delta_\gamma(\phi).$$

Let the complexity of the chromatic diversity be indexed in terms of minimal length of the ‘programs’ to regenerate the distribution $\Gamma_s$ via possible self-similarity processes within the locally Gaussian color space $\Gamma$. By invoking a multitude of Brownian motion processes to simulate the uncertainty due to such a stochastic-computational diversity, we have the probability distribution for capturing $\Xi_s$ in terms of the solution to the following partial differential equation [10]:

$$\frac{1}{2} \Delta \varphi_\rho (\gamma|s) + \rho [\chi_s - \varphi_\rho (\gamma|s)] = 0.$$  \hspace{1cm} (8)

In this equation, the complexity factor $\rho$ is adjusted to the fractal dimension $\rho = \log \|\text{RGB}\|$. To the smooth distribution $\varphi_\rho (\gamma|s)$, we can extend the zero-cross method [15] to yield the following Laplacian-Gaussian boundary [10]:

$$\partial^g \Gamma_s = \left\{ \gamma \in \Gamma : \varphi_\rho (\gamma|s) = \frac{1}{e} \max_{\gamma \in \Gamma} \varphi_\rho (\gamma|s) \right\}.$$

By using the samples $s$ shown in (b) of Fig. 2, we have the capturing probability $\varphi_\rho (\gamma|s)$ with the fractal boundary $\partial^g \Gamma_s$ as shown in Fig. 5.

Noticing that the attractor of the iterated function system is expanded nondeterministically towards the fixed points which should not be located interior nor exterior of the attractor [9], we can identify the control parameter of the chromatic diversity through the allocation of the fixed point on the Laplacian-Gaussian boundary $\partial^g \Gamma_s$. The identification process is divided into the following three steps. First, a possible fixed point $\tilde{\gamma}_f$ is located on $\partial^g \Gamma_s$ and expanded via the following successive scheme:

$$\tilde{\Gamma}_{f+1}^f = \tilde{\Gamma}_f^f \cup \tilde{\Gamma}_f^f, \quad \tilde{\Gamma}_0^f = \left\{ \tilde{\gamma}_f \right\}.$$  \hspace{1cm} (9)
Figure 7: Matting by As-is Primary: $f^\text{RGB}_\omega \mapsto \tilde{\pi}_i$

where the increment is selected by the following nondeterministic algorithm

$$
\tilde{d}_t = \begin{cases}
\tilde{\partial}_t \gamma = \gamma & \text{if } \partial_t \gamma < \gamma \wedge \gamma < \tilde{\gamma}
\text{ and }
\tilde{\partial}_t \gamma \in \partial^2 \Xi - \tilde{\gamma},
\end{cases}
$$

with respect to $\tilde{\eta} (\gamma, \Lambda) = \min_{\lambda \in \Lambda} |\gamma - \lambda|$. Next, a subset $\{ \tilde{\gamma}_k \}$ satisfying the following conditions is selected as an estimate of the vertices

$$
p [\phi (\tilde{\gamma}_k)] = \max_{\tilde{\gamma}_k} p [\phi (\gamma)],
$$

where $\tilde{\gamma}_k$ denotes associated $\Gamma$-space expansion satisfying

$$
\tilde{\gamma}_i = \tilde{\gamma}_i + \kappa d \tilde{\gamma}_i,
$$

$$
d \tilde{\gamma}_i = \sum_{j \neq i} (\tilde{\gamma}_j - \tilde{\gamma}_i) + 3 \tilde{\gamma}_i,
$$

with control parameter $k$ satisfying $|\tilde{\gamma}_i + \kappa d \tilde{\gamma}_i| = 1$; through the $\Gamma$-space expansion, the fixed points $\{ \tilde{\gamma}_k \}$ are mutually separated within the space spanning possible diversity of nonnegative chromatic information; by invoking the consistency constraint (10), the fixed points nearest to the self images of the $\Gamma$-space expansion are maintained as the vertices. Noticing the structural stability throughout the $\Gamma$-space expansion steps, we can exploit the vertices as a robust information in the unknown degeneration processes. As the result, we can select a feature colors invariant with respect to unknown degeneration process towards the observation $\chi_s$. The scheme (9) combined with (10) yields a set of fixed points $\{ \tilde{\gamma}_k \}$ to be associated with a set of contraction mapping for regenerating the distribution $\Gamma_s$. Define the as-is primary $\Pi = \{ \tilde{\pi}_i \}$ by

$$
\tilde{\pi}_i = \tilde{\pi}_i + \pi_i \text{RGB},
$$

$$
3 \tilde{\pi}_i^2 + 2 \tilde{\pi}_i \text{RGB} \cdot \pi_i + |\tilde{\pi}_i|^2 = 1,
$$

where the saturation of each as-is primary $\tilde{\pi}_i$ is maximized within the support of ‘nonnegative’ color matching process via the constraint (11b). By definition, we can restore the unknown degeneration process along the vectors $\{ \tilde{\gamma}_i \mapsto \tilde{\pi}_i \}$ as shown in Fig. 6; a set of as-is primary $\Pi = \{ \tilde{\pi}_r, \tilde{\pi}_\text{rg}, \tilde{\pi}_g, \tilde{\pi}_\text{gb}, \tilde{\pi}_b \}$ is detected from the scene image (Fig. 2); adding to the trichromatic primary, $\tilde{\pi}_\text{rg}$ was separated from $\text{R}$; $\text{G}$ and $\text{B}$ are shifted to jointly generate another new primary $\tilde{\pi}_\text{gb}$. Thus, we have a robust imaging parameter to regenerate all possible chromatic diversity under significant degeneration process within the locally Gaussian color space.

4 Saliency Pattern Detection (up link)

As indicated in Fig. 3, the notabilia to be locally associated with the as-is primary are maintained via the statistical compression; our inherent vision can recognize landmarks (a post, red- and green sign patterns to be identified within symbolic world) and distractive objects (a child and a bicycle) in the
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Figure 8: Complexity Reduction via $\hat{\psi}_\omega$-filtering

matted version of the scene image. Despite such a generativity, however, it is not easy to recognize such landmarks through global matching of the as-is primary; as displayed in Fig. 7, various distractive patterns are confused with a degenerated versions of primary color. Thus, the as-is primary should be transferred through a generic focus control mechanism to imitate a global-to-local matching process at the first visit.

Noticing that entire the distribution $\Gamma_\alpha$ is nondeterministically associated with the as-is primary via a family of fractal dynamics, let the probability of RGB selection, $\{(\phi_c)^2, c \in \text{RGB}\}$ be extended to the selection of as-is primary as follows:

$$p(\hat{\pi}_i|\omega) = \frac{p(\phi_\omega|\hat{\pi}_i) \cdot p(\hat{\pi}_i)}{\sum_{\hat{\pi}_i \in \hat{\Pi}} p(\phi_\omega|\hat{\pi}_i) p(\hat{\pi}_i)}, \quad \text{(12)}$$

where $p(\phi_\omega|\hat{\pi}_i) = (\phi_\omega^\top \hat{\pi}_i)^2$ and $p(\hat{\pi}_i) = 1/||\hat{\Pi}||$. Since the probabilistic complexity arising in the adapted preference to the as-is primary can be indexed in terms of the following Shannon’s entropy:

$$\hat{\mathcal{H}}_\omega = -\sum_{\hat{\pi}_i \in \hat{\Pi}} p(\hat{\pi}_i|\phi_\omega) \log p(\hat{\pi}_i|\phi_\omega), \quad \text{(13)}$$

with associated mean value $\hat{\mathcal{H}}_m$, we have the following evaluation of the chromatic saliency:

$$\hat{\psi}_\omega = 1 - \exp \left[ -\frac{1}{2} \left( \frac{\log ||\hat{\Pi}|| - \hat{\mathcal{H}}_\omega}{\log ||\hat{\Pi}|| - \hat{\mathcal{H}}_m} \right)^2 \right], \quad \text{(14)}$$

where the computation cost is estimated in terms of the Shannon entropy such that $\hat{\mathcal{H}}_\omega \in \left[ 0, \log ||\hat{\Pi}|| \right]$. The pixelwise index $\hat{\psi}_\omega$ was applied to the scene image (Fig. 2) to extract the saliency distribution as indicated in Fig. 8. As exhibited in this figure, we have an enhancement with respect to scene specific notabilia; despite significant degeneration from original colors, various types of human readable landmarks were detected based on the saliency index $\hat{\psi}_\omega$: through the comparison with Fig. 3, it is verified that the $\hat{\psi}_\omega$-filter is well controlled by global parameter $\hat{\Pi}$ to maintain sign and/or design; in contrast with direct matting (Fig. 7), the nondeterministic association with the representatives $\{\phi_j^*\}$ via $\hat{\psi}_\omega$ indexing is effective to confine the landmark images; This implies that the as-is primaries uploaded by the probe vehicle provides robust cue to control the focus of on-vehicle vision of future visitors via $\hat{\Pi} \rightarrow \phi^*$ association.

5 Saliency Pattern Re-Detection (down-link)

Let the as-is primary $\hat{\Pi}$ be transferred through the geographics annotation and consider the re-detection of notabilia within the distribution $\hat{\mathcal{f}}_\omega^{\text{RGB}}$ of visitor’s view. By applying probed evaluation (12) to the scene specific representation of the chromatic diversity $\hat{\phi}_\omega = \hat{\mathcal{f}}_\omega^{\text{RGB}} / |\hat{\mathcal{f}}_\omega^{\text{RGB}}|$, we have an in-situ evaluation of the
chromatic saliency with respect to the transferred information $\hat{\Pi}$ as follows:

$$
\hat{\psi}_\omega = 1 - \exp \left[ -\frac{1}{2} \left( \frac{\log \|\hat{\Pi}\| - \tilde{\mathcal{H}}_\omega}{\log \|\Pi\| - \tilde{\mathcal{H}}_m} \right)^2 \right],
$$

with $\tilde{\mathcal{H}}_\omega = -\sum_{\hat{\pi}_i \in \hat{\Pi}} p(\hat{\pi}_i | \hat{\phi}_\omega) \log p(\hat{\pi}_i | \hat{\phi}_\omega)$ and mean $\tilde{\mathcal{H}}_m$.

The complexity reduction by using $\hat{\psi}_\omega$- and $\tilde{\psi}_\omega$-filters are compared Fig. 9; saliency patterns extracted from various scene images is indicated in (a); from each scene image, the saliency index $\hat{\psi}_\omega$ is extracted and applied to the RGB distribution $f_{\omega \text{RGB}}$ to yield filtered image $\hat{\psi}_\omega f_{\omega \text{RGB}}$ as indicated in (b); the complexity reduction by the $\hat{\psi}_\omega$-filtering is compared with (c) where the as-is primary transferred from the scene (1) is applied to the RGB distribution in visitors views (2)–(5) to generate another version of saliency patterns with respect to $\hat{\psi}_\omega$. In all the views (2)–(6), the $\hat{\psi}_\omega$-filtering maintains notabilia exhibiting visual saliency with respect to the $\hat{\psi}_\omega f_{\omega \text{RGB}}$-image. Simultaneously, the $\hat{\psi}_\omega$- and $\tilde{\psi}_\omega$-filters equivalently confine fixed sign patterns to identify the post office, e.g., in noisy background; in some cases, the low-
articulated regions are indicated by white lines; by allocating the fixed points of fractal models as illustrated in Figs. 10 and 11, respectively; in figure 10, the fractal contours of with respect to \( \hat{\omega} \) upper subwindows. In these figures, (a) and (b) indicate the articulation results of filtered distributions on the contours in the main windows and the chromatic diversity of the regions are displayed in associated **identified with fractal attractor as indicated in Fig. 11 where the fixed points are marked by red circles.**

**Table 1: Relative Complexity Reduction**

| Scene                  | \( dS_\hat{\psi} \) | \( dS_\hat{\varphi} \) | \( dS_G \) | \( ||\hat{\Pi}|| \) |
|------------------------|-----------------------|--------------------------|------------|----------------------|
| post office (1)        | 2.814177              | -                        | 1.405944   | 4                    |
| shopping street (2)    | 1.958979              | 1.251333                 | 1.109258   | 4                    |
| digital zoom (3)       | 2.247838              | 0.609302                 | 1.016533   | 4                    |
| afternoon sun (4)      | 2.567482              | 1.681750                 | 1.490656   | 4                    |
| evening breeze (5)     | 2.790921              | 1.242093                 | 1.430227   | 5                    |

key visualizations are ‘highlighted’ via the \( \hat{\psi}_\omega \)-filtering for compensating inherent perception capability. By using adaptive global-to-local matching scheme \( \hat{\Pi} \mapsto \hat{\phi}^* \), thus, we can utilize transferred as-is primary for the re-detection of saliency patterns in noisy background.

6 Results

The significance of the \( \hat{\psi}_\omega \)- and \( \hat{\varphi}_\omega \)-filtering as focus control information is summarized in Table 1 where the reduction of the computational complexity is evaluated in terms of the relative index \( dS_\hat{\psi} = S_G - S_\hat{\psi} \); \( S_G \) designate the Shannon’s entropy with respect to the uniform distribution and the gray level distribution, respectively; \( S_\hat{\psi} \) and \( S_G \) stand for the entropy with respect to the normalized version of the saliency indices \( \hat{\psi}_\omega \) and \( \hat{\varphi}_\omega \) associated with viewer specific and transferred as-is primary systems, respectively, i.e.,

\[
S(\cdot) = -\frac{1}{C(\cdot)} \int_{\Omega} (\cdot) \log (\cdot) d\omega + \log C(\cdot),
\]

with normalization constant \( C(\cdot) \).

As shown in this table, the \( \hat{\psi}_\omega \)-filter concentrate the information distributed in the image plane into a set of saliency patterns of average size \( 7 < e^{dS_\hat{\psi}} < 16 \); this implies that the length of decision steps for selecting a saliency pattern is reduce to \( 1/7–1/16 \) of random search in image plane; in natural scenes, the estimate is improved to 25%–42% of the complexity reduction by using gray level distribution. Table 1 indicates that the decision steps for the pattern re-detection using transferred as-is primary is reduced as well; the evaluation in terms of \( dS_\hat{\psi} \) is no less than 25%–40% of \( \hat{\psi}_\omega \)-based reduction. This implies that the \( \hat{\psi}_\omega \)-filter maintains considerable effectiveness in the complexity reduction.

In the view (3) where a section of the view (2) is magnified via digital re-sampling and the view (5) observed through ‘low-key’ imaging, on the other hand, the \( \hat{\psi}_\omega \)-filter can restore some saliency patterns confused in the gray scale imaging. Thus, the probe vehicles can transfer the as-is primary to future visitors as an effective cue to anticipative focus control in distractive and/or ill-conditioned scenes.

7 Discussions – transferability of as-is primary

The \( \hat{\psi}_\omega \)-filter provides a computational basis of pattern articulation in the visitors views as well as the pattern detection via \( \psi_\omega \)-filtering. To re-detect the saliency patterns, the fixed point allocation scheme (Fig. 5+ 6) is applied to \( \psi_\omega f_{\omega}^{\text{RGB}} \) and \( \psi_\omega f_{\omega}^{\text{RGB}} \)-images; detected fixed points \( \Omega^f = \{ \omega_i^f \} \) is used to design the associated set of contraction mappings \( \nu = \{ \mu_i \}, \mu_i : \Omega \to \Omega \) of the form: \( \mu_i (\omega) = \frac{1}{2} [ \omega + \omega_i^f ] \).

Thus, we have an iterated function system [1] to articulate the saliency distribution \( \left( \hat{\psi}_\omega f_{\omega}^{\text{RGB}} , \hat{\varphi}_\omega f_{\omega}^{\text{RGB}} \right) \) within the scene images.

A part of fractal articulation results are shown in Figs. 10 – 13 where, as an example, the saliency indices are restricted to the pixels nearest to \( \hat{\omega}_k \); i.e., \( \psi_\omega = \hat{\psi}_\omega = 0 \) at non-nearest pixels. The restricted versions of the saliency distributions \( \left( \hat{\psi}_\omega f_{\omega}^{\text{RGB}} , \hat{\varphi}_\omega f_{\omega}^{\text{RGB}} \right) \) are articulated in the image plane and the space of fractal models as illustrated in Figs. 10 and 11, respectively; in figure 10, the fractal contours of articulated regions are indicated by white lines; by allocating the fixed points \( \{ \omega_i^f \} \), each region is identified with fractal attractor as indicated in Fig. 11 where the fixed points are marked by red circles on the contours in the main windows and the chromatic diversity of the regions are displayed in associated upper subwindows. In these figures, (a) and (b) indicate the articulation results of filtered distributions with respect to \( \psi_\omega \)- and \( \hat{\psi}_\omega \)-indices respectively.
The identified fractal attractors are matched with the perspective of prober’s and visitor’s views. To this end, fractal models are projected to the depth probability induced the scene images [13]; (a) and (b) of Fig. 12 illustrate that each mapping set yields closed links (red lines) connecting the local maxima of the depth information extracted from prober’s- and visitor’s views (green circles). As a result, we have fractal models spanning connected regions perpendicular to the roadway areas.

Figure 13 displays similar results on the transferability of the as-is primary to the views (3)–(5); even in scene images corrupted through digital re-sampling (3) and/or low-key imaging (5), the transferred as-is primary well detects and localizes saliency patterns within the perspective of the scenes. These results imply that the probe vehicle can transfer the generator of scene specific notabilia as a cue to the re-detection by future visitors equipped with the adaptive global-to-local matching scheme.

Thus, we can exploit the as-is primary as a transferable information spanning significant discrepancy of ambient light and photographing conditions. The robustness of the as-is primary implies that various types notabilia objects can be annotated in terms of specific as-is primary to be downloaded by future visitors. The implementation of object-pattern association environment within the cooperative geographics annotation scheme is left to future investigations.

8 Concluding Remarks

A nondeterministic color matching scheme was introduced for saliency-based pattern re-detection spanning significant discrepancy of ambient light. Inherent susceptibility to chromatic diversity supporting landmark sign/design can be well imitated via detection and adaptive projection of as-is primary. Detected and re-detected saliency patterns maintain various types of notabilia to be annotated in the local geographics. Through the landmark annotation based on the as-is primary, the probe vehicles can transfer focus control parameter for the over-the-horizon cooperation.

References

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(a) $\tilde{\psi}_{\omega}^{\text{RGB}_\omega}$-based Design in Visitor’s View: down-link (1)→(2)

(b) $\tilde{\psi}_{\omega}^{\text{RGB}_\omega}$-based Design in Prober’s View: up-link (1)

Figure 11: Fractal Articulation of Naturally Complex Scene

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Figure 12: Consistency of Fractal Articulation with Scene Specific Perspective

Figure 13: Saliency-based Notabilia Re-Detection