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Image Complexity Analysis for Self-Tuning Pattern Regeneration in Open Environment Knowledge Projection

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ABSTRACT

A non-deterministic image feature detection scheme is presented for interactive scene analysis. The image feature is identified with an attractor generated by a class of self-similar mappings. The mapping parameter is estimated through complexity analysis of non-linear diffusion field excited by observed imagery.

INTRODUCTORY REMARKS

Various decision support systems cooperatively generate environment description as the basis of schematic instruction [6], [7], [8]. Following computation model of cognition process [10], [12], the instruction schematics can be represented by a system of propositions defined on symbols deeply rooted in encountered environment. As the referents of propositions, the objects should be coded in terms of generic features. In articulating not-yet-identified scene, on the other hand, the object should be coded in terms of observables. For denotatively preassigned objects, geometric models are available as feature representations: 3D contours as location invariants [4] and 2D grammar as phrase-structure invatiants [5]. However, morphological variations of object result in the Gödel's trap [7]: The geometric model must be *a priori* adjusted to not-yet-encountered objects by an all-seeing-designer (Fig.1). In this paper, a non-deterministic scheme is introduced for object description. This scheme successively regenerates observed pattern via the coordination of image complexity.

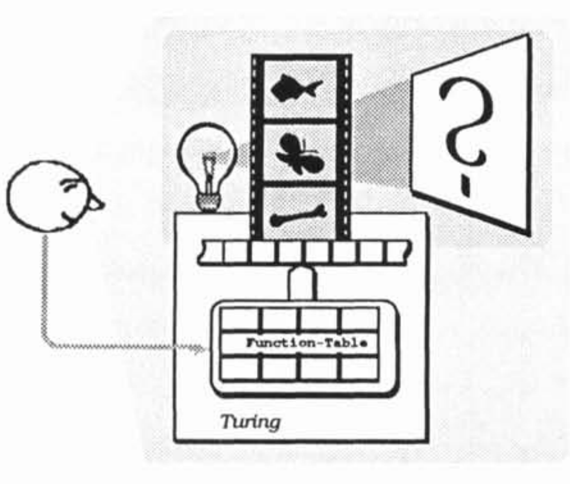


Fig.1. Gödel's Trap

NON-DETERMINISTIC OBJECT MODEL

Mathematically, this Gödel's trap is a paraphrase of the undecidability theorem [3]: *For an arbitrary fixed algorithm* π*, there exists an observable and indicatable pattern* Λ *that is undecidable by* π. Despite the intrinsic non-determinism, the detection scheme should be programmable within the framework of the formally closed systems: *For a fixed set of observable-indicatable patterns* $\{\Lambda_i,\ i=1,2,3...N\}$*, there exists an algorithm* π *for which arbitrary* Λ_i*, 1,2,3,...N, are decidable.* To overcome this undecidability-programmability contradiction, the detection scheme invokes a non-deterministic description as an *a priori* object model. The basic idea of non-deterministic modeling is to describe the objects in terms of the invariant sets in joint iconic-symbolic feature space (Fig.2). In this description, the image feature is represented as a fractal attractor non-deterministically generated by a class of self-similar mappings [2]. The introduction of implicit representation implies that the contour patterns of not-yet-identified objects are anticipatively visualized *prior to* the completion of object modeling. In understanding an unstructured environment, the attractor model is combined with the ownership description [11] and the attractor of the motion [1] to generate an integrated *a posteriori* object description.

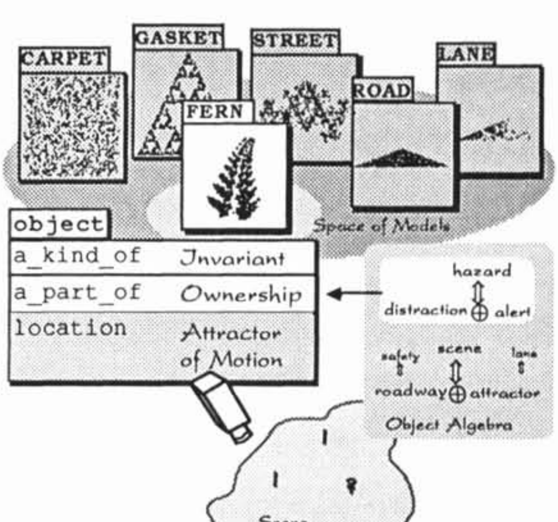


Fig.2. Non-Deterministic Object Model

PATTERN REGENERATION PROCESS

Let Λ be an observation of an object contour via a dynamic version of the zero-cross scheme formulated by the following

Edge Extraction Process:

$$\Lambda = \{\ \lambda \in \Sigma \mid |\Delta u| = 0 \ and \ |\nabla u| > 0\}, \quad (1a)$$

$$\frac{\partial u}{\partial t} = \Delta u + \alpha[v-u], \ t \in T=[T_0,T_1], \quad (1b)$$

where Σ and v denote the image field and the gray level distribution in Σ, respectively. The response and resolution of observation Λ to object image v are simultaneously controlled by the positive parameter α. When observed contour Λ is smooth, the pattern location, designated by θ, is computed by the following

Tracking Scheme:

$$\frac{\partial \varphi}{\partial t} = \Delta\varphi - \gamma\varphi, \ \varphi=1 \text{ on } \Lambda, \quad (2a)$$

$$\frac{d\theta}{dt} = \int_{\Sigma} W\delta[\theta]\nabla\phi ds, \quad (2b)$$

where $\delta[\theta]$ and W denote Dirac's delta distribution and a properly chosen gain matrix [1]. The initial value of the location estimate $\theta_0=\theta(T_0)$ is chosen as the minimal point of the diffusion field φ. For arbitrary $\gamma>0$, the detection scheme (2) subjected to smooth and convex pattern Λ yields unique minimal point θ_0.

Consider a dissipative structure σ generated on irreversible thermodynamic system (2a) under the excitation of complicated pattern Λ. In this system, the energy flow q_φ is evoked between the excitation $\chi[\Lambda]$ and the heat sink (Fig.3). The control parameter γ in detection scheme (2) is adjusted so as to coordinate the complexity associated with fractal attractor σ and observable Λ.

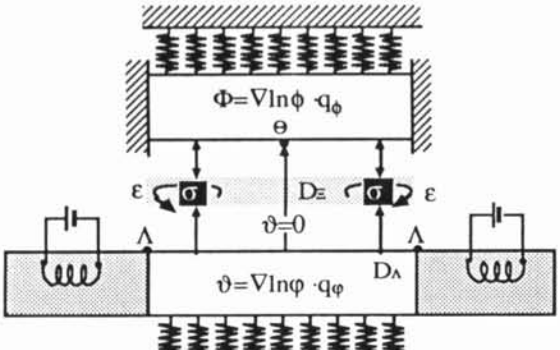


Fig.3. Irreversible Thermodynamic System

Let Θ be the 2D distribution of the following

Null Entropy Generation Points:

$$\Theta = \{\theta \in \Sigma \mid \nabla \ln\varphi \cdot q_\varphi = 0\}. \quad (3)$$

By definition, the distribution Θ is a finitely extended version of the location θ for generalized pattern Λ. The discrete distribution Θ is specified in terms of the local minimum points without *a priori* information concerning not-yet-identified objects. Thus, we have the structural measure Θ for *a posteriori* complexity evaluation of the observation Λ.

For regenerating the observation Λ, the discrete distribution Θ is disintegrated via the following

Field Interaction Scheme:

$$\frac{\partial \phi}{\partial t} = \Delta\phi - (\frac{1}{\gamma})\phi, \ \phi=1 \text{ on } \{\Theta\}_\tau \cup \Xi_\tau[\Lambda], \quad (4)$$

for $\tau \le t < \tau+1$. In Eq. (4b), $\Xi_\tau[\Lambda]$ denotes the following

Equi-Field Set:

$$\Xi_\tau[\Lambda] = \{\ \xi \in \Sigma \mid |\Delta\phi_\tau| > 0, |\Delta\varphi_\tau| > 0, |\phi_\tau - \varphi_\tau| = 0\ \}. \quad (5)$$

Noting that $\Xi_\tau[\Lambda]$ converges to a self-similar approximation of Λ, define

$$\sigma = \lim_{\tau \to \infty} \Xi_\tau[\Lambda]. \quad (6)$$

As a dissipative structure in non-linear diffusion system (4), the invariant pattern σ regenerates the observation Λ. Define

$$P(\sigma|\Lambda) = \frac{\int_{\sigma\cap\Sigma} \varphi(s)ds}{\int_{\Sigma} \chi[\Lambda]ds}, \quad (7)$$

for arbitrary regeneration σ and observation Λ. This $P(\sigma|\Lambda)$ satisfies the following

Properties of Conditional Probabilities:

$$0 \le P(\sigma|\Lambda) \le P(\Lambda|\Lambda) \le 1, \quad (8a)$$

$$P(\cup\sigma_i|\Lambda) = \Sigma P(\sigma_i|\Lambda), \ \sigma_i \cap \sigma_j = \varnothing, \quad (8b)$$

$$P(\sigma|\cup\Lambda_i) = \Sigma P(\sigma|\Lambda_i), \ \Lambda_i \cap \Lambda_j = \varnothing, P(\Lambda_i) = P(\Lambda_j). \quad (8c)$$

Then, we have the measure $P(\sigma|\Lambda)$ for *a posteriori* evaluation of the complexity of pattern regeneration process (5).

STRUCTURAL COMPLEXITY ANALYSIS

Despite the non-anticipation, the discrete feature Θ yields a cue to consistency evaluation of mapping candidates. Let a class of self similar mappings $\Pi=\{\pi_i, i=1,2,...\}$ be selected as a priori information. Then, the a posteriori consistency of the mapping $\pi\in\Pi$ with attractor Λ is evaluated through self correlation analysis for the range of the projection $\pi[\mathcal{D}[\Theta]]$, where $\mathcal{D}[\Theta]=\{\theta\in\Theta \mid \pi[\theta]\in\Theta\}$ denotes the domain of the mapping π.

First, the consistency of the a priori class Π is analyzed through the detection of the following

Invariant Sub-class:

$$\Pi^0 = \{\pi^0\in\Pi \mid \exists\mathcal{D}^0\subset\mathcal{D}[\Theta], \pi^0[\mathcal{D}^0]=\mathcal{D}^0\}. \tag{9}$$

Next, the collage theorem for the Iterated Function Systems [2] is invoked to estimate the correlation between the discrete patterns Θ and $\mathcal{R}[\Theta]=\pi[\mathcal{D}[\Theta]]\cap\mathcal{D}[\Theta]$, i.e., the restriction of the range of projection into itself. Then, the consistency of the mapping π is estimated based on the following

Collage Error Evaluation:

$$h(\Theta,\mathcal{R}[\Theta]) \leq \frac{h(1-C[\Theta])}{1-L[\Theta]}, \tag{10a}$$

$$C[\Theta] = \frac{\|\mathcal{R}[\Theta]\|}{\|\mathcal{D}[\Theta]\|}, \tag{10b}$$

$$L[\Theta] = \frac{\|\mathcal{R}[\Theta]\|}{\|\pi[\mathcal{D}[\Theta]]\|}, \tag{10c}$$

where $h(\bullet,\bullet)$ and $\|\bullet\|$ denote the Hausdorff metric and size of the discrete pattern. In Eq. (10), $C[\Theta]$ and $L[\Theta]$ denote the coverage factor and the contractivity factor, respectively. Hence, a best fit mapping $\pi^*\in\Pi^0\subset\Pi$ is determined through a correlation computation on a finite pattern Θ.

PATTERN COMPLEXITY ANALYSIS

The adjustable parameter γ in pattern regeneration process (4) is controlled so as to coordinate the complexities associated with the approximation σ and the mapping π^*. This implies that, for adjusting the regeneration process (4), explicit specification of the mapping is not needed. The dissipative pattern σ well approximates the attractor Λ based only on the estimate of the "program length" for mapping description. The complexity associated with the non-deterministic regeneration process (4) is evaluated in terms of the probability of the dissipative pattern σ conditioned by the observation Λ. By the estimation of the conditional probability $P(\sigma|\Lambda)=\int_{\sigma\cap\Sigma}\varphi ds / \int_{\Sigma}\chi[\Lambda]ds$ and by applying Bayesian calculus to the following

Fifty-Fifty Criterion:

$$P(\sigma|\Lambda) = P(\neg\Lambda|\pi), \tag{11}$$

we have a guideline for adjusting γ in terms of the following

Fixed Point Problem:

$$P(\sigma|\Lambda) = \frac{P(\pi)}{P(\Lambda)}[1 - P(\sigma|\Lambda)]. \tag{12}$$

In Eq. (12) the ratio $P(\pi)/P(\Lambda)$, designated by relative complexity, indicates the description reduction of iconic pattern Λ by the constraint of mappings π. The relative complexity $P(\pi)/P(\Lambda)$ is evaluated using the computational complexity ρ defined by the following

Complexity Coordination Rule:

$$\rho = \min\{\log_2|\varepsilon|-1, \log_2|\pi|\}, \tag{13}$$

where $|\varepsilon|$ and $|\pi|$ denote the length of error messages ε and mapping π. In Eq. (13), the error message is coded for specifying the σ–Λ disparity independent of the location of Θ [9]. Equation (13) implies that both overfitting mappings and too random deviations are rejected during regeneration. Thus, the computational complexity ρ provides the consistency evaluation of reasonable mappings π on the initial condition $\sigma_0=\Theta$. Hence, the conditional probability $P(\sigma|\Lambda)$ computed as the fixed point associated with the computational complexity ρ, yields the target for the diffused pattern φ. In other words, the control parameter γ is adjusted to reduce the error

$$\hat{P}(\sigma|\Lambda)-\lambda, \tag{14a}$$

$$\lambda = \frac{\int_{\sigma\cap\Sigma}\varphi ds}{\int_{\Sigma}\chi[\Lambda]ds}, \tag{14b}$$

where $\hat{P}(\sigma|\Lambda)$ denotes the solution to the fixed point problem (12) for a fixed relative complexity $P(\pi)/P(\Lambda)$. This implicit control process is formulated in terms of the following

Search Scheme:

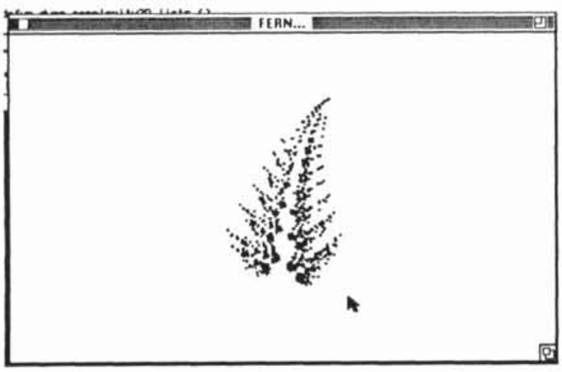
$$\gamma \leftarrow \kappa^*\rho[1-\lambda], \tag{15a}$$

$$\frac{\gamma}{\lambda} \leftarrow \kappa^*. \tag{15b}$$

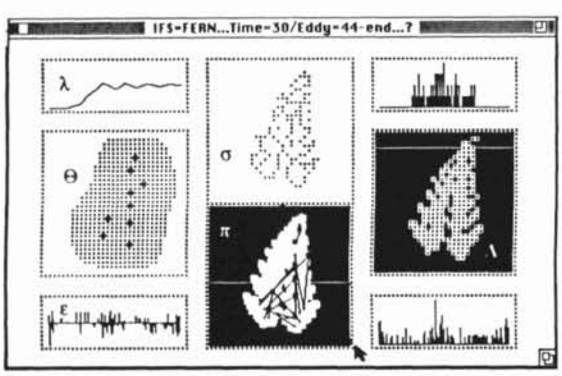
Equation (14) successively updates the process parameter γ and associated conditional probability estimate $\lambda \approx P(\sigma|\Lambda)$ simultaneously.

SIMULATION STUDIES

The pattern regeneration process is verified through a series of simulation studies. An example of simulation results is shown in Fig.4. In this simulation, a fractal pattern, "FERN", is generated by Monte Carlo simulation and is regenerated through the proposed scheme. The observed fractal pattern Λ is well-approximated by the dissipative structure σ generated by the non-linear diffusion system. In diffused pattern φ, the distribution of null entropy generation points Θ is detected. A set of mapping candidates was successively projected on this bottom up information Θ-distribution. In the figure, the self similarity mapping π associated with the "FERN" pattern is successfully projected. Simultaneously, the disparity of the dissipative pattern ε and the length of the mapping π are evaluated to adjust the regeneration process to the target pattern Λ. As a result of this complexity coordination, the fit of the dissipative structure σ, the regenerated pattern, to the target attractor Λ is optimized so that the resulting conditional probability $P(\sigma|\Lambda)$ satisfies the fifty-fifty criterion.



(a) Encountered Pattern



(b) Mapping Selection
Fig.4 Simulation Results

CONCLUDING REMARKS

A non-deterministic detection scheme was presented for image features with self-similarity. In this scheme, the pattern to be detected is regenerated as the dissipative structure on non-linear diffusion field. The self-similar mapping is identified through the computational analysis of the null entropy generation points.

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