Content-Based Image Indexing and Retrieval: A Syntactical Approach

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Abstract

This paper presents a syntactical approach to the content-based indexing and retrieval of images. Studies on the content-based indexing/retrieval of images were motivated to derive from the visual features inside images a set of objective criteria for the indexing/retrieval of the images. The existing content-based image indexing and retrieval methods, however, use in an unstructured manner the visual features such as edge elements, color histogram, texture distribution, and so on. As a result, both indexing and retrieval are not efficient and effective, compared with the text-based methods. A new hierarchical structure representation is presented in this paper. Since the hierarchical structure is generated with a data-driven approach, an objective description on an image can be obtained. The potential application of the hierarchical structure to the content-based image indexing and retrieval is discussed.

1 Introduction

The traditional hierarchical structure representation has been defined on the basis of human perception [1]. It might be used as a model for a top-down approach to the image analysis but can never be applied to solving the content-based indexing and retrieval problems. This is because the content-based indexing and retrieval of an image basically require an objective description on the image. The traditional hierarchical structure representation, however, is strongly dependent on the subjective interpretation given by each individual person. Given a single image, a different person may give a different interpretation to the image and thus may represent the image with a completely different hierarchical structure.

Studies on the content-based indexing of images are originally motivated by the needs of eliminating the subjective biases involved in the text-based indices. Most of the existing content-based indexing approaches, however, are limited to the use of low-level visual features [2]. Since the low-level visual features are usually used in an unstructured and not well-organized manner, the retrieval is no more than an inefficient pattern matching process.

This paper presents a new hierarchical structure representation. The new hierarchical structure representation is generated with a completely data-driven approach and hence is an objective description on an image. The rest of this paper is organized as follows. Section 2 describes in detail the process of how the new hierarchical structure representation is defined. Section 3 shows the algorithms for the generation of our new hierarchical structure representation. Section 4 discusses with experimental results on the potential application of our hierarchical structure representation to the content-based indexing and retrieval. Section 5 concludes the paper with the discussion on the future work.

2 Hierarchical Structure Representation

In this section, we first give a formal definition on the primitive components of our structure representation and then define two basic spatial relationships. Finally, we define the new structure representation by generalizing the definition of the basic spatial relationships.

2.1 Generalized connected component (GCC)

2.1.1 Definition of GCC

Definition 1: A GCC σ is a set of pixels so that

$$\forall p \exists q (P(p, q) \wedge M(q, \sigma) \wedge C(p, q, f) \Rightarrow M(p, \sigma)) \quad (1)$$

where p and q are two different pixels, $P(p, q)$ means that p and q share a kind of uniform property such as intensity, color, etc., $M(q, \sigma)$ means $q \in \sigma$, and $C(p, q, f)$ is a connectivity constraint between p and q .

The connectivity constraint is recursively defined with the following boundary condition:

$$\forall u \forall v (N(u, v, f) \wedge P(u, v) \Rightarrow C(u, v, f)) \quad (2)$$

where $N(u, v, f)$ means that pixels u and v neighbor with each other, f specifies the neighborhood⁴. The recursion part is:

$$\forall u \forall v \exists r (P(u, r) \wedge P(r, v) \wedge C(u, r, f) \wedge C(r, v, f) \Rightarrow C(u, v, f)) \quad (3)$$

2.1.2 Region/Segment vs. GCC

According to **Def. 1**, a GCC is a pixel group. Since region and segment have been widely-used concepts for pixel groups, it is naturally enquired why it is necessary to introduce a new concept. The reason that GCC's are not replaceable by regions/segments is as follows:

- **semantics levels:** region is a high-level concept, while segment is a low-level concept.
- **connectivity:** region completely satisfies the connectivity constraints in **Def. 1**, while segment partially satisfies the constraints.

GCC is a concept in the middle position in terms of both the semantics levels and pixels connectivity.

2.2 Basic Spatial Relationships

Given an image Δ , let Δ' denote the border of Δ . $\Sigma = \{\sigma_i \mid 1 \leq i \leq |\Sigma|\}$ is obtained from Δ .

Definition 2: The border σ'_i of σ_i is a subset of σ_i such that $\sigma'_i = \{p \mid \exists q \in \Delta' \exists \pi \sigma_i \cap \pi = \{p\}\}$, where π is a path⁵ between p and q and $\{p\}$ denotes a set with a single pixel p .

Definition 3:

$$surrounded(\sigma_i, \sigma_j) \iff \forall p (N_b(p, \sigma'_i) \Rightarrow M(p, \sigma_j)) \quad (4)$$

where $surrounded(\sigma_i, \sigma_j)$ means that σ_i is surrounded by σ_j and σ_j surrounds σ_i . Note that (4) implies $\sigma'_i \cap \Delta' = \phi$.

Definition 4:

$$joint(\sigma_i, \sigma_j) \iff (\exists p (N_b(p, \sigma'_i) \wedge M(p, \sigma_j)) \vee \exists q (N_b(q, \sigma'_j) \wedge M(q, \sigma_i))) \quad (5)$$

where $joint(\sigma_i, \sigma_j)$ means that σ_i and σ_j are joint with each other.

The meaning of N_b in (4) and (5) is as follows. Given a pixel $q \in \sigma'_i$, let $q_1, q_2, \dots, q_8$ denote the eight neighbors of q in clockwise order. Suppose σ'_i is tracked clockwise. $N_b(q_m, \sigma'_i)$ is true iff $q_m \notin \sigma'_i$ but $q_{(m+1)(mod 8)} \in \sigma'_i$. Obviously, $joint(\sigma_i, \sigma_j) = joint(\sigma_j, \sigma_i)$ but $surrounded(\sigma_i, \sigma_j) \neq surrounded(\sigma_j, \sigma_i)$. It can be seen that $surrounded(\sigma_i, \sigma_j) \Rightarrow joint(\sigma_i, \sigma_j)$.

Definition 5:

$$unrelated(\sigma_i, \sigma_j) \iff \neg(surrounded(\sigma_i, \sigma_j) \vee surrounded(\sigma_j, \sigma_i) \vee joint(\sigma_i, \sigma_j)) \quad (6)$$

2.3 Graph Representation of Σ

Definition 6: The *graph representation* of Σ is a graph $G = (V, A)$, where $V = \{v_1, \dots, v_{|\Sigma|}\}$ is a set of vertices corresponding to $\{\sigma_1, \dots, \sigma_{|\Sigma|}\}$ and $A = \{\dots, a_{ij}, \dots\}$ a set of arcs such that a_{ij} is an undirected arc

between v_i and v_j when $joint(\sigma_i, \sigma_j)$ is true but a directed arc from v_j to v_i when $surrounded(\sigma_i, \sigma_j)$ is true and vice versa.

Theoretically, as long as $|\Sigma|$ is finite, the number of the possible structures of Σ will be finite. However, experimental results have shown that a graph representation has the following shortcomings⁶:

- A graph representation is not a hierarchical structure in most cases.
- The correspondence between isostructural Σ 's and their graph representations may not be one-to-one.
- The number of the possible structures and also the corresponding graph representations overwhelmingly increase as $|\Sigma|$ increases.

This is because a graph representation is a completely machine-oriented structure representation.

2.4 Partition of Σ

Let $\Psi_\Sigma = \{\Sigma_m \mid 1 \leq m \leq |\Psi_\Sigma|\}$ be a set which consists of the subsets of Σ such that in the case $|\Sigma_m| > 1$, Σ_m satisfies:

$$\forall \sigma_p \exists \sigma_q (M(\sigma_p, \Sigma_m) \wedge M(\sigma_q, \Sigma_m) \Rightarrow joint(\sigma_p, \sigma_q)) \quad (7)$$

Definition 7: $\psi_\Sigma \subseteq \Psi_\Sigma$ is a partition of Σ iff $\forall \Sigma_p, \forall \Sigma_q \in \psi_\Sigma \Sigma_p \cap \Sigma_q = \phi$ and $\bigcup_{i=1}^{|\psi_\Sigma|} \Sigma_i = \Sigma$.

Obviously, $\{\{\sigma_i\} \mid 1 \leq i \leq |\Sigma|\}$ is the case that $\forall \Sigma_m \in \psi_\Sigma |\Sigma_m| = 1$ and hence a candidate for ψ_Σ . ψ_Σ is non-deterministic unless $|\Sigma| = 1$.

Let Δ_m be a set of pixels corresponding to $\Sigma_m \in \Psi_\Sigma$ such that $\Delta_m = \bigcup_{i=1}^{|\Sigma_m|} \sigma_{m_i}$. The difference between Δ_m and Σ_m is the same as that between Δ and Σ , i.e., the elements of Δ_m and Δ are pixels but the elements of Σ_m and Σ are GCC's. **Def. 2** is generalized as follows:

Definition 8: The border Δ'_m of Δ_m is a subset of Δ_m such that $\Delta'_m = \{p \mid \exists q \in \Delta' \exists \pi \Delta_m \cap \pi = \{p\}\}$, where π is a path between p and q and $\{p\}$ denotes a set with a single pixel p .

The correspondence between Σ_m and Δ'_m is not always one-to-one because we may have $\exists \sigma_p \in \Sigma_m$ but $\sigma_p \cap \Delta'_m = \phi$. The following constraint is thus defined to uniquely determine $\Sigma_m \in \Psi_\Sigma$ for a given Δ'_m .

Constraint 1: $\Sigma_m = \{\sigma_i \mid \sigma_i \cap \Delta'_m \neq \phi\}$.

Now we can generalize **Def. 3** as follows:

Definition 9: $\forall \Sigma_m \in \Psi_\Sigma$ satisfying **Con.1** and $\forall \Sigma_n \in \Psi_\Sigma$, $surrounded(\Sigma_m, \Sigma_n)$ is true iff $\forall \sigma_q \in \Sigma_n \sigma_q \cap B_{\Delta'_m} \neq \phi$ and $\Delta_n \supseteq B_{\Delta'_m}$, where $B_{\Delta'_m} = \{p \mid N_b(p, \Delta'_m)\}$.

The following are the human-oriented constraints, which actually determine a procedure for the generation of a unique partition ψ_Σ^U .

Constraint 2: If $\Sigma_1 = \{\sigma_i \mid \sigma_i \cap \Delta' \neq \emptyset\}$ then $\Sigma_1 \in \psi_\Sigma^U$.

Constraint 3: $\forall \Sigma_m \in \psi_\Sigma^U$ with $m \geq 1$ and $\forall \Sigma_n \in \Psi_\Sigma$ with $n > m$, if $\exists S_{\Sigma_m} \subseteq \Sigma_m$ and $\text{surrounded}(\Sigma_n, S_{\Sigma_m})$ is true then $\Sigma_n \in \psi_\Sigma^U$.

2.5 A Tree Structure Representation of Σ

Definition 10: $T = (V_T, A_T)$, where $V_T = \{V_1, \dots, V_{|\psi_\Sigma^U|}\}$ is a set of vertices corresponding to $\{\Sigma_1, \dots, \Sigma_{|\psi_\Sigma^U|}\}$ and $A_T = \{\dots, A_{ij}, \dots\}$ a set of directed arcs such that A_{ij} is directed from V_j to V_i in the case that $\text{surrounded}(\Sigma_i, S_{\Sigma_j})$ with $S_{\Sigma_j} \subseteq \Sigma_j$ is true and vice versa.

The difference between $T = (V_T, A_T)$ and $G = (V, A)$ is as follows.

- $V = \{v_1, \dots, v_i, \dots, v_{|\Sigma|}\}$, where v_i corresponds to σ_i and $|\Sigma|$ is the total number of GCC's in Σ , but $V_T = \{V_1, \dots, V_i, \dots, V_{|\psi_\Sigma^U|}\}$, where $V_i = \{X_i, E_i\}$ is a graph which corresponds to Σ_i and $|\psi_\Sigma^U|$ is the total number of graphs. Further, $X_i = \{x_{i1}, \dots, x_{i|\Sigma_i|}\}$ is a set of vertices representing $\{\sigma_{i1}, \dots, \sigma_{i|\Sigma_i|}\}$ and $E_i = \{\dots, e_{(ip)(iq)}, \dots\}$ a set of undirected arcs such that $e_{(ip)(iq)}$ linking x_{ip} and x_{iq} corresponds to the case that $\text{joint}(\sigma_{ip}, \sigma_{iq})$ is true.
- $A = \{\dots, a_{ij}, \dots\}$, where a_{ij} can be either directed or undirected depending on whether $\text{joint}(\sigma_i, \sigma_j)$ or $\text{surrounded}(\sigma_i, \sigma_j)$ (or $\text{surrounded}(\sigma_j, \sigma_i)$) is true. On the other hand, $A_T = \{\dots, A_{ij}, \dots\}$, where A_{ij} can only be a directed arc because either $\text{surrounded}(\Sigma_i, S_{\Sigma_j})$ with $S_{\Sigma_j} \subseteq \Sigma_j$ or $\text{surrounded}(\Sigma_j, S_{\Sigma_i})$ with $S_{\Sigma_i} \subseteq \Sigma_i$ must be true. In the case that $\text{surrounded}(\Sigma_j, \Sigma_i)$ is true, A_{ij} is directed from V_i to V_j . In the case that $\text{surrounded}(\Sigma_j, S_{\Sigma_i})$ with $S_{\Sigma_i} \subset \Sigma_i$ is true, however, A_{ij} is directed from a subgraph but not the whole of V_i to V_j , where the subgraph corresponds to S_{Σ_i} .

3 Content-based indexing and retrieval

The transformation from Δ to Σ is a pixel grouping process. We simplify the pixel grouping problem by using a document image database created from Ref.7. Fig.1 shows a computer-generated Σ and its corresponding structure representation.

Fig.2(a) shows a key image whose structure representation is used as a key for a retrieval experiment. Fig.2(b) shows the first candidate retrieved. Fig.2(c) shows the second candidate. The retrieval process is

basically a matching processing between the structure representations. The results shown in Fig.2(b) and Fig.2(c) are obtained by using the following to parameters.

- $|F_{\Sigma_j}|$, $F_{\Sigma_j} = \{\Sigma_i \mid \text{surrounded}(\Sigma_i, S_{\Sigma_j})\}$, i.e., the number of elements which are surrounded by the same element.
- $|\Sigma_i|$, the number of GCC's in Σ_i , i.e., a particular element.

4 Conclusion

A new structure representation of an image has been presented. Except for the human-oriented constraints for uniquely generating GCC groups, the overall process for the generation of the structure representation is a data-driven process. Since the structure representation is a hierarchy, a coarse-to-fine pattern matching is possible.

Figure 1: An example image and its structure representation.

Figure 2: (a) a key image for an image retrieval experiment; (b) the first candidate retrieved; (c) the second candidate retrieved.

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