In the past, people gathered cultural information from physical objects (such as books, sculptures, statues, and paintings). Now, digital collections have become common practice for most cultural-content providers. However, as the amount of the Web's cultural content grows, search and retrieval procedures for that content become increasingly difficult. Moreover, Web users need more efficient ways to access huge amounts of content. So, researchers have proposed sophisticated browsing and viewing technologies, raising the need for detailed metadata that effectively describes the cultural content. Several annotation standards have been developed and implemented, and Semantic Web technologies provide a solution for the semantic description of collections on the Web. Unfortunately, the semantic annotation of cultural content is time consuming and expensive, making it one of the main difficulties of cultural-content publication. Therefore, the need for automatic or semi-automatic analysis and classification of cultural assets has emerged.

Recent advances in Web technologies that ensure quick, effective information distribution have created the ideal terrain for spreading various cultures through cultural-content presentation. Nowadays, we are witnessing the publication of a huge amount of cultural information on the Web.

To meet this need, researchers have proposed using image analysis methods (for some examples, see the sidebar on the next page). However, these methods use domain knowledge for only low-level analysis. Also, two main difficulties have arisen in using image analysis to automate annotation and classification of cultural digital assets. The first is the failure of semantic image segmentation and image analysis algorithms in some real-world conditions. This is due to the high variability of content and environmental parameters (luminance and so on), which makes the problem complex. The second difficulty is the extensive and vague nature of domain knowledge (at least for some cultural content), which complicates formal knowledge representation and reasoning.

However, some cultural domains are appropriate for automatic analysis and classification methods. Byzantine icon art is one of them. The predefined image content and the low variability of the image characteristics support the successful application of image analysis methods. Consequently, we've developed a system that exploits traditional...

**Semantic Classification of Byzantine Icons**

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This system uses fuzzy description logics and patterns to automatically determine the sacred figure depicted in an icon.
The July 2008 IEEE Signal Processing Magazine presented some particularly interesting applications of image analysis to the cultural-heritage domain. Alejandro Ribes and his colleagues described problems concerning the design of multispectral cameras as well as the analysis of the Mona Lisa in the context of the digitization of paintings. Anna Pelagotti and her colleagues proposed a novel multispectral digital-imaging technique for clustering image regions in a set of images containing similar characteristics when exposed to electromagnetic radiation. Their technique provides material localization and identification over a painting’s entire surface. C. Richard Johnson and his colleagues described how three research groups developed systems that identify artists on the basis of brushwork characteristics that art historians use for authentication. Finally, Howard Leung and his colleagues reported on the preservation of ancient Chinese calligraphy.

References

Byzantine Iconography
Byzantine art refers to the art of Eastern Orthodox states that were concurrent with the Byzantine Empire. Certain artistic traditions born in the Byzantine Empire, particularly regarding icon painting and church architecture, have continued in Greece, Bulgaria, Russia, and other Eastern Orthodox countries up to the present. The icons usually depict sacred figures from the Christian faith, such as Jesus, the Virgin Mary, the apostles, and the saints.

At the beginning of the 17th century, iconography manuals represented the most important source of inspiration for icon painters. The 16th-century monk Dionysios from Founa is credited as the author of the prototypical manual, Interpretation of the Byzantine Art. In it, he defines the rules and iconographic patterns that painters still use to create icons.

Byzantine iconography follows a unique convention of painting. The artistic language of Byzantine painters is characterized by apparent simplicity, emphasized flatness, unnatural and symbolic colors, lack of perspective, and strange proportions. The sacred figures are set beyond real time and real space through the use of gold backgrounds. The most important figure in an icon is depicted frontally, focusing on the eyes and facial expression. This segment contains the sacred figure’s most distinguishable features—for example, hair and beard style. The remaining segments contain the sacred figure’s body, focusing on the hands and arms. The body can be depicted in different poses—for example, standing, sitting, from the head to the waist, and from the head to the thorax.

The head should be elliptical. The major axis is along the vertical part of the head and is equal to four times the height of the nose (H). (According to Dionysios, the nose serves as the metric for producing harmonious facial and body proportions.) The minor axis is along the horizontal and is equal to 3H. The head segment can be separated into four equal vertical sections of height H. The hair is in the first part, the forehead is in the second, the nose is in the third, and the area between the mustache and the chin is in the fourth.

A Byzantine painter applies four base colors in layers on the face segment. The darkening is a dark color for the base of the face segment and the darkest shadows. The proplasmos is a less-dark color for lighter shadows. The sarkoma is for flesh, and the lightening is for highlights, containing a good amount of white and being light enough to show light against the base color. The absolute value of these colors differs from icon to icon.

From Art Manual to Semantic Representation
Although the knowledge in Dionysios’s manual concerns vague concepts such as “long hair,” “young face,” and so on, it’s quite strict and formally described. Consequently,
we can create an ontological representation of this knowledge using OWL. In this way, the ontology’s axiomatic skeleton will provide the terminology and restrictions for Byzantine icons.

The only problem is that even a well-tuned image analysis algorithm can’t produce perfect results for a wide set of data with different characteristics. Moreover, many Byzantine icons might be misinterpreted owing to their age, further affecting the results. Finally, the vague nature of terms such as distance, color, and length introduces fuzziness in the categorization of objects. For example, sometimes a sacred figure represents a young face, but only to a certain degree. In such cases, standard description logics (DLs) are insufficient because they can’t deal with vague, uncertain information. To handle such problems, researchers have proposed fuzzy DLs, based on fuzzy sets and fuzzy logic, which are suitable for handling imprecise information.3

To classify the important facial features of Byzantine icons and detect the sacred figures having specific characteristics, we combine image analysis algorithms with the expressive power of fuzzy DLs. Using the rules and patterns described in Dionysios’s manual, we constructed a fuzzy knowledge base that’s populated by the results of image analysis of the digitized paintings. Using fuzzy reasoning and on the basis of the defined terminology, our system can classify the figures in Byzantine icons.

**The Icon Classification System**

Figure 1 shows the general architecture of our Byzantine icon classification system. It consists of the Byzantine icon analysis subsystem and the knowledge representation and reasoning subsystem.

**Byzantine Icon Analysis**

This subsystem performs the image processing and analysis tasks necessary to detect a set of primitive concepts and properties (such as face and long hair) and form assertional knowledge that semantically describes the icon’s content. It consists of modules for semantic segmentation, feature extraction, and semantic interpretation.

The first step of system development was the interpretation, with the aid of Byzantine iconography experts, of Dionysios’s manual. This procedure provided us with a large set of heuristics that facilitated the design of the subsystem modules and helped us select the most appropriate semantic segmentation and feature extraction methods.

**Semantic segmentation.** This module divides the icon into regions visualizing the icon’s physical objects and their parts. The first step of semantic segmentation is face detection. For this, we adopted a fast method based on support vector decision functions.4 This method first uses integral imaging for very fast feature evaluation based on Haar basis functions. Then, it uses a simple, efficient classifier based on the AdaBoost learning algorithm to select a small number of critical visual features from a very large set of potential features. Finally, this method combines classifiers in a “cascade,” quickly discarding the image’s background regions while concentrating computation on promising face-like regions. An example of this method’s results is the green rectangle in the first image of the face detection box in Figure 2 (see next page).

The next step is localization of the eyes. Because the nose’s height should be equal to the distance of one retina from the other, that distance is a critical parameter for segmentation. The semantic-segmentation module performs eye localization with the
Face detection extracts the face and its basic components (nose and eyes).

Face component detection detects the most important components of the face (beard, moustache, cheek, forehead, and hair, respectively).

Base color analysis extracts the base color layers (darking, proplasmos, sarkoma, and lightening).

Figure 2. Image analysis. First, the algorithm detects the sacred figure’s face region, eyes, and nose. Then, it extracts the hair, forehead, cheek, mustache, and beard parts together with the face’s base color layers. Further analysis of the extracted parts provides information about characteristic features. Finally, the algorithm produces a semantic interpretation for each of these features, together with formal assertions.

Feature extraction. This module automatically extracts features from the segmented parts, providing additional information regarding each part’s length, color, shape, and texture. This information constitutes the characteristic values of the features, providing an image description set (see the image-description section of the feature extraction box in Figure 2).

Dionysios assigns four features to hair:

- **s1**: Length(s1) = 2.8*H
- **s2**: darkning(s1) = 88%

Face detection extracts the face and its basic components (nose and eyes).

Weights and model eyes to determine an eye’s presence and position (indicated by the red and green dots in the second image in the face detection box of Figure 2).

After eye localization, the module detects the nose. Let H denote the distance between the eyes and consequently the nose’s length. According to Dionysios, the nose starts on a small horizontal line whose center is a distance of H/5 below the midpoint between the eyes. We use a Hough transform to find this line. Therefore, we determine the nose’s ending line by applying a Hough transform at a distance H down vertically from the starting line.

The computation of H leads to the detection of the face’s other main components—the hair, forehead, cheek, moustache, and beard—because they are well defined in Dionysios’s manual.

The module detects the four base colors by applying an Otsu segmentation algorithm to a restricted area of the face segment (see the base color analysis box in Figure 2), determining a range of intensity values for the pixels.

To segment each part of the face, we use H together with Dionysios’s proportion guidelines to define the seeds for graph-cut segmentation. The cost functions used as soft constraints incorporate boundary and part information for each of the five segmented parts. To achieve segmentation of each part, we compute the minimum cut that’s the global optimum among all the segmentations satisfying the constraints (see the face-component-detection box in Figure 2).

Semantic interpretation gives meaning to specific features, properties, and relationships of face components with the aid of fuzzy partitions.
• color (dark, gray, or white),
• density (thin or thick),
• length (above the ears or below the ears, and whether the figure has a braid on the left, right, or both shoulders), and
• form (straight, wild, or curly).

The feature extraction module categorizes hair color (see Figure 2, feature extraction, segment s1) using the intervals of Otsu segmentation. It estimates the density and form by combining a Canny edge detector and a morphological filter and by evaluating the mean value of the curvatures of the detected edges. It finds the hair’s length using \( H \) together with Dionysios’s proportion guidelines.

Next, the module determines information about the sacred figure’s age by computing the number of wrinkles on the forehead (s2). Using the Hough transform, the module defines the number of vertical and horizontal lines in the forehead, which represent the wrinkles. A young sacred figure has zero or few wrinkles, whereas an older sacred figure has many.

The cheek (s3) provides additional information about age. According to Dionysios, a small number of wrinkles on the larger (left or right) part of the cheek indicates a young sacred figure. Conversely, an older sacred figure’s cheek will have a greater number of wrinkles (and therefore a greater proportion of the colors used for shadows).

Finally, the module defines the feature sets for the mustache (s4) and beard (s5). Using techniques similar to those for hair analysis, it analyzes the mustache’s color and shape. It also extracts information on the beard’s length (short, not very long, long, down to the waist, or down to the knees), color (fair or dark), form (straight, wild, or curly) and shape (sharp, circle-like, circle, wide, or fluffy).

Semantic interpretation. This module represents the extracted information in terms of the sacred-figure ontology.

Representing the face and its main components is straightforward: we simply write assertions such as s1: Hair (see the semantic-interpretation box in Figure 2). However, each component’s properties are vague. For example, you can’t always directly determine on the basis of length whether the sacred figure has long hair. This difficulty is due to the vagueness of the definition of length and the imprecision introduced by feature extraction (see, for example, the result of the segmentation of the hair in the feature extraction box in Figure 2). Nevertheless, we can express an assertion in a fuzzy manner, with the aid of fuzzy set theory. This procedure is critical for the knowledge representation system.

Suppose that a specific feature’s values lie in the interval \( X \). A fuzzy set \( A \) of \( X \) associates each value \( x \) of \( X \) to a real number in the interval \([0, 1]\), with the value of \( f_A(x) \) at \( x \) representing the grade of membership of \( x \) in \( A \). So, we define an appropriate fuzzy partition (a set of fuzzy sets) of \( X \) and connect each fuzzy set of the partition with a subconcept of the terminology, defined by that fuzzy set’s property. For example, having extracted the value \( 2.8H \) for the length of hair (s1), we determine that s1 has a membership value of 0.7 for AboveEarsHair and 0.3 for BelowEarsHair (see the graph in the semantic-interpretation box in Figure 2). The definition of the fuzzy partitions is based on the heuristics extracted from Dionysios’s manual.

Knowledge Representation and Reasoning

This subsystem consists of terminological and assertional knowledge and a reasoning engine.

These types of knowledge are the basic components of a knowledge-based system based on DLs, a structured knowledge-representation formalism with decidable-reasoning algorithms. DLs have become popular, especially because of their use in the Semantic Web (as in OWL DL, for example). DLs represent a domain’s important notions as concept and role descriptions. To do this, DLs use a set of concept and role constructors on the basic elements of a domain-specific alphabet. This alphabet consists of a set of individuals (objects) constituting the domain, a set of atomic concepts describing the individuals, and a set of atomic roles that relate the individuals. The concept and role constructors that are used indicate the expressive power and the name of the specific DL. Here, we use SHIN, an expressive subset of OWL DL that employs concept negation, intersection, and union; existential and universal quantifiers; transitive and inverse roles; role hierarchy; and number restrictions.

Terminological and assertional knowledge. The terminological knowledge is an ontological representation of the knowledge in Dionysios’s manual. The assertional knowledge is a formal set of assertions describing a specific icon in terms of the terminological knowledge. For example, the terminology contains axiomatic knowledge such as “a Jesus Face is depicted as a young face with long, straight, thick,
black hair and a short, straight, thick, black beard,” whereas “the face depicted in the icon is a face with long hair in some degree” is a relative assertion.

The knowledge base has two main components. The terminological component (TBox) describes the relevant notions of the application domain by stating properties of concepts and roles and their interrelations. TBox is actually a set of concept inclusion axioms of the form $C \subseteq D$, where $D$ is a superconcept of $C$, and concept equivalence axioms of the form $C \equiv D$, where $C$ is equivalent to $D$.

The assertional component (ABox) describes a concrete world by stating properties of individuals and their specific interrelations. To deal with the vagueness introduced in our case, we use f-SHIN, a fuzzy extension of SHIN.3 In f-SHIN, ABox is a finite set of fuzzy assertions of the form $(a : C \bowtie n)$, $(a, b : R \bowtie n)$, where $\bowtie$ stands for $\leq$, $>$, or $<$, for $a, b \in I$. Intuitively, a fuzzy assertion of the form $(a : C \geq n)$ means that the membership degree of $a$ to concept $C$ is at least equal to $n$. (A formal definition of the syntax and semantics of fuzzy DLs appears elsewhere.3,10)

In the Byzantine-icon-analysis domain, the individuals are the segments that the semantic-segmentation module extracted. The DL concepts classifying the individuals are determined by the properties measured as features during feature extraction (for example, BlackHair and AboveEarsHair). The DL roles mainly describe partonomic (mereological) hierarchies and spatial relations (for example, the axiom $\text{isLeftOf} = \text{isRightOf}$ indicates that the role isLeftOf is the inverse of isRightOf, and the axioms Trans($\text{isLeftOf}$) and Trans($\text{isAboveOf}$) indicate that isLeftOf and isRightOf are transitive).

The terminology’s main concepts are Figure, Face, and FaceComponent. They’re connected with the partonomic role hasPart and its subroles hasSegment and hasComponent, to indicate whether a segment is a subsegment of another segment and so on. Using these roles, we describe the partonomic hierarchy as follows:

$\text{Face} \equiv \forall \text{hasComponent}.\text{FaceComponent}$

$\text{Figure} = \exists \text{hasSegment}.\text{Face}$

$\text{FaceComponent} \subseteq \text{Beard} \sqcup \text{Cheek} \sqcup \text{Forehead} \sqcup \text{Hair} \sqcup \text{Mustache}$

We describe relevant assertions as follows:

$\langle s: \text{Face} \geq 1.0 \rangle$

$\langle s1: \text{Hair} \geq 1.0 \rangle$

$\langle (s, s1): \text{hasSegment} \geq 1.0 \rangle$

... The taxonomy is constructed using the properties measured as features during feature extraction. Here are some examples of terminological axioms defining the concept hierarchy:

AboveEarsHair $\subseteq$ Hair

OldCheek $\subseteq$ Cheek

OldForehead $\subseteq$ Forehead

HairyBeard $\subseteq$ Beard

Restrictions concerning the taxonomy mainly describe disjointness and exhaustiveness, forming axioms such as

AboveEarsHair $\subseteq \neg$ BelowEarsHair

Hair $\subseteq$ AboveEarsHair $\sqcup$ BelowEarsHair

Using these concepts, we define more expressive descriptions that specify some specific face characteristics on the basis of Dionysios’s manual. For example, we define a young man’s face as

JesusFace $\equiv \exists \text{hasComponent}.\text{BlackHair} \sqcap \exists \text{hasComponent}.(\text{NotVeryLongBeard} \sqcap \text{BlackBeard})$ $\sqcap \exists \text{hasComponent}.\text{YoungForehead} \sqcap \exists \text{hasPart}.\text{YoungCheek} \sqcap \exists \text{hasPart}.\text{BlackMustache}$

We similarly define concepts specifying the characteristics of some popular sacred figures. For example, we define JesusFace as

JesusFace $\equiv \exists \text{hasComponent}.\text{YoungMansFace} \sqcap \exists \text{hasComponent}.(\text{BraidOnTheLeftShoulder} \sqcap \text{HairyHair} \sqcap \text{StraightHair}) \sqcap \exists \text{hasComponent}.(\text{CircleLikeBeard} \sqcap \text{StraightBeard})$

The reasoning engine. This module uses the terminological knowledge and the assertions to recognize the sacred figure. Our system uses FiRE, the Fuzzy Reasoning Engine (www.image.ece.ntua.gr/~nsimou/FiRE), which fully supports f-SHIN.

Figure 3 illustrates how the engine performs reasoning and classification for recognizing Jesus as the sacred figure. We use FiRE’s greatest lower bound (GLB) reasoning service, which evaluates an individual’s greatest possible degree of participation in a concept. The concepts of interest in this case, YoungMansFace and JesusFace, only include conjunc-
tions, so we use the fuzzy intersection operator for the minimum. So, the GLB of segment s (the face) in YoungMansFace is 0.82, whereas the GLB of segment s in JesusFace is 0.78. In other words, the extracted features indicate that the face depicted is YoungMansFace to a degree of 0.82 and is JesusFace to a degree of 0.78.

**Results**

We evaluated our system on a database, provided by the Mount Sinai Foundation in Greece, containing 2,000 digitized Byzantine icons dating back to the 13th century. The icons depict 50 different characters; according to Dionysios, each character has specific facial features that makes him or her distinguishable.

Evaluation of the Byzantine-icon-analysis subsystem produced promising results. The subsystem’s mean response time was approximately 15 seconds on a typical PC.

In the semantic-segmentation module, the face detection submodule reached 80 percent accuracy. In most cases, the failure occurred in icons with a destroyed face area. If the submodule detected the face, it almost always detected the eyes and nose. The base-color-analysis submodule defined the color model used by the icon’s artist, which the feature extraction module later used. Using the nose’s height, which can be easily determined, and taking into account the manual’s rules, the face-component-detection submodule estimated the positions of the background and foreground pixels for every part of the face. These positions constituted the input to the graph-cut algorithm. This submodule achieved 96 percent accuracy.

The feature extraction module extracted features for every icon segment. Then, using the fuzzy partitions, the semantic-interpretation module interpreted each segment’s specific features and properties and the relationship of face parts. Thus, that module determined each feature’s degree of membership in a specific class, thereby creating an image description.

To evaluate overall system performance, we used precision and recall. Table 1 (on the next page) presents results for 20 of the sacred-figure classes. The more distinctive facial features the sacred figure in a class contained, the better our method performed (for YoungMansFace hasComponent.
BlackHair ∩ hasComponent.
1. (NotVeryLongBeard ∧ BlackBeard)
∩ hasComponent.YoungForehead
∩ hasPart.YoungCheek ∧ hasPart.
BlackMoustache

JesusFace = YoungMansFace ∩
hasComponent.(BraidOnTheLeftShoulder
∩ HairyHair ∩ StraightHair)
∩ hasComponent.(CircleLikeBeard
∩ StraightBeard)

s: Face
s1: Hair ...
(s, s1): hasComponent ...

s1: BraidOnTheLeftShoulder = 0.78
s1: HairyHair = 0.96
s1: StraightHair = 0.86
s1: BlackHair = 0.88
s2: YoungForehead = 0.82
s3: YoungCheek = 0.87
s4: StraightMoustache = 1.0
s4: BlackMoustache = 0.83
s5: CircleLikeBeard = 0.79
s5: StraightBeard = 0.92
s5: NotVeryLongBeard = 1.0
s5: BlackBeard = 0.84

Figure 3. A reasoning example. The extracted information from image analysis constitutes the assertional component (ABox) of the knowledge base; the terminological component (TBox) is defined on the basis of Fourna’s specification. These components form the input to the fuzzy reasoning engine, which infers information about the icon.
example, for the Jesus class). Conversely, our method performed worse on figures with similar facial features, such as women.

We’re developing a version of our system that takes into account information about clothes associated with specific types of figures (such as apostles, kings, angels, and monks) and clothing accessories (kerchiefs and so on) and nonclothing accessories (books, crosses, and so on) associated with specific sacred figures. For example, the system could incorporate the knowledge that icons of the Virgin Mary depict her wearing a kerchief with three stars. Such information might help in classifying figures with similar facial features.

Furthermore, an integrated version of our system could eventually date icons and attribute them to a particular artist or artistic school, on the basis of features specific to each artistic period. Such information can help classify an icon even if the specific sacred figure is difficult to recognize. We’re also investigating applying our method to other art movements such as impressionism, trying to classify paintings on the basis of unmixed colors and dense textures.

Acknowledgments
Our research has been partly supported by the MORFES (extraction and modeling of figure in Byzantine paintings of Mount Sinai monuments using measures) project, funded by the EU and the Greek Secretariat for Research and Development. We thank the Mount Sinai Foundation for providing access to the rich data set and especially archeologist Dimitris Kalomirakis for his participation in knowledge extraction and his continuing support during this research. Finally, we thank the anonymous reviewers for their constructive comments.

References

Table 1. Evaluation of the icon classification system.

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