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Intra-dimensional feature diagnosticity in the Fuzzy Feature Contrast Model

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Abstract

Similarity assessment is a basic operation to query images in a large database. Based on fuzzy logic, Santini and Jain extended Tversky's Feature Contrast Model (FCM) to measure image similarity, and developed the Fuzzy Feature Contrast Model (FFCM). In this paper, we analyze the distinction between FCM and FFCM in terms of feature representations, and point out that the intra-dimensional feature diagnosticity in the FCM has not been considered in the FFCM. Consequently, similarity measures of the FFCM are positively correlated with visual feature intensities. In order to depress the positive correlation and preserve the original idea of the FCM where possible, we propose an extension of the FFCM called the Diagnostic Fuzzy Feature Contrast Model (DFFCM). Both the feature diagnosticity and feature intensity are employed to measure the image similarity by the DFFCM. The simulated experimental results demonstrated that the impact of the feature intensity on similarity measures of the DFFCM was weaker than that of the FFCM. Experimental results based on synthetic and real-word image databases showed that the DFFCM outperformed the FFCM in terms of image similarity measures.

Keywords: Similarity measures; Feature Contrast; Image retrieval

1. Introduction

As the old saying goes, an image is worth a thousand words. The diversity of image semantics makes it challenging to search images in a large image database. Given representations of images, measuring similarity between images is a fundamental operation to query images in databases [1]. Recently, much attention has been paid to extend the well-known Feature Contrast Model (FCM) to measure image similarity in order to better retrieve images [1–8]. Unlike Minkowski-type geometric distances, the FCM expresses the similarity measurement as a contrast, or a linear combination, of common and distinctive features. Each object is represented as a set of binary features where each feature value denotes presence or absence of the feature in the set. The binary feature set is suitable for describing discrete qualitative features (e.g., semantic features). For continuous quantitative feature (e.g., visual features), one needs a complex mechanism to transform them into a set of binary features using prior knowledge of feature structure and the task under investigation. For instance, Gati and Tversky used a chain of features to describe some continuous features [9]. Therefore, it is very difficult to directly apply the FCM to measure image similarity using visual features. The reason is that enumeration of visual features is impossible or problematic in a large image database, e.g., enumerating all kinds of colors [1]. In order to avoid this limitation, Santini and Jain developed an extension of the FCM called Fuzzy Feature Contrast Model (FFCM), which was utilized to measure image

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similarity using visual features. For a given visual feature, the complex feature transformation mechanism was replaced by a fuzzy membership function. Consequently, each image can be represented as a multidimensional feature vector [1].

Although the dimensional representation of the FFCM is very useful to represent visual features of images, it is one of two basic assumptions that were challenged by Tversky in developing the FCM [10]. In this paper, we analyze the distinction between FCM and FFCM in terms of feature representations, and point out that the intra-dimensional feature diagnosticity in the FCM has not been considered in the FFCM. Consequently, for a given feature, the similarity measurement of FFCM is positively correlated with the feature intensity in the sensing of following two aspects. One is that the self-similarity increases with the intensity of a feature. The other is that an image with a larger feature value would be judged to be more similar to that with a less feature value, even when two images are of equal distances to a reference image. In order to depress the positive correlation of the FFCM and preserve the original idea of the FCM where possible, we propose an extension of the FFCM called the Diagnostic Fuzzy Feature Contrast Model (DFFCM). The DFFCM employs both the feature diagnosticity and feature intensity to measure the similarity between images.

The rest of this paper is organized as follows. In Section 2, related works are reviewed. The intra-dimensional feature diagnosticity is discussed in Section 3. Experimental results and discussion are given in Section 4. Some conclusions are drawn in Section 5.

2. Related works

Human assessments of similarity are foundational to cognition. In the field of psychology, similarity has been an active research topic for many years. In a review [11], four main approaches to similarity measures were outlined: geometric [12–14], feature-theoretic [9,10,15,16], alignment-based [17–19] and transformational [20,21]. Geometric and feature-theoretic models are often analyzed in terms of their contradictory assumptions. The geometric model, e.g., classic Multidimensional Scaling (MDS) [12–14], assume that similarity conforms the metric axiom, i.e., self-similarity, minimality, symmetry and triangle inequality. The Minkowski-type geometric distances are widely used in real applications. However, some psychologists have questioned the metric axiom [8–10,17,22]. For example, the constancy of self-similarity has been refuted in [10,22]. A number of investigators have questioned the symmetry with direct similarity experiments [8,10,17,22] and observed asymmetries in confusion matrices [23]. The triangle inequality is not held in some cases [10].

Along with the development of image retrieval, many psychological approaches to similarity, in particular non-metric similarity measures, are utilized to analyze or assess similarity between images. The latent reasons consist in: (1) human similarity assessment in the nature might be non-metric; (2) those Minkowski-type geometric distances are often not good enough to characterize the similarity between images. Based on fuzzy logic, Tversky's feature-theoretic similarity was extended to measure image similarity [1–8]. Mojsilović et al. [24] employed MDS to analyze the semantic similarity among images. Alignment-based similarity measures were generalized to measure similarity between images with multiple regions [25,26]. More attention has been paid to learn similarity measures through relevance feedback [27–33]. In the rest of this section, we confine ourselves to review the FCM and its fuzzy extensions for measuring image similarity.

2.1. Feature Contrast Model

Tversky challenged the dimensional and metric assumption, which underlies the geometric similarity models, and developed an alternative feature matching approach to the analysis of similarity relations [10]. Feature Contrast Model is one representation form of feature matching functions, which satisfies assumptions of feature matching processing. Let A, B and C be the feature sets of objects a, b and c, respectively. $S(a,b)$ is a similarity measure between objects a and b. Tversky postulated five assumptions for his similarity theory, i.e., matching, monotonicity and independence, solvability and invariance [10]. Any function, which satisfies the first two assumptions, is called matching function $F(x)$:

(1) *Matching*: $S(a,b) = F(A \cap B, A - B, B - A)$. That is to say the similarity measure could be expressed as a function of three parameters: common features, which are shared by two objects (i.e., $A \cap B$) and distinctive features, which belong to only one of the two objects (i.e., $A - B$ and $B - A$).
(2) *Monotonicity*: $S(a,b) > S(a,c)$ wherever $A \cap C \subseteq A \cap B$, $A - B \subseteq A - C$ and $B - A \subseteq C - A$. That implies the similarity would increase with the number of common features and decrease with that of distinctive features.

As a simple form of matching function, the FCM is given by

$$S(a,b) = \theta f(A \cap B) - \alpha f(A - B) - \beta f(B - A), \tag{1}$$

where $f(X)$ is a non-negative salience function of the feature set X, and θ, α and β are three non-negative constants. In addition, Tversky also developed a ratio matching function

$$S(a,b) = \frac{f(A \cap B)}{f(A \cap B) + \alpha f(A - B) + \beta f(B - A)}, \tag{2}$$

where the similarity is normalized so that its value lies between 0 and 1.

In the FCM, each stimulus is characterized by the presence or absence of a feature and all relevant features are specified according to prior knowledge of feature structures