Knowledge-Based Systems 000 (2017) 1–18

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

Knowledge-leveraged transfer fuzzy *C*-Means for texture image segmentation with self-adaptive cluster prototype matching

Pengjiang Qian [a,b,c], Kaifa Zhao [a], Yizhang Jiang [a,*], Kuan-Hao Su [b,c], Zhaohong Deng [a], Shitong Wang [a], Raymond F. Muzic Jr. [b,c]

[a] *School of Digital Media, Jiangnan University, Wuxi, Jiangsu, PR China*
[b] *Case Center for Imaging Research, Case Western Reserve University, Cleveland, Ohio, USA*
[c] *Department of Radiology, University Hospitals Cleveland Medical Center, Case Western Reserve University, Cleveland, Ohio, USA*

ARTICLE INFO

Article history:
Received 5 September 2016
Revised 15 May 2017
Accepted 18 May 2017
Available online xxx

Keywords:
Fuzzy C-means (FCM)
Transfer learning
Knowledge transfer
Image segmentation
Data heterogeneity

ABSTRACT

We study a novel fuzzy clustering method to improve the segmentation performance on the target texture image by leveraging the knowledge from a prior texture image. Two knowledge transfer mechanisms, i.e. *knowledge-leveraged prototype transfer* (KL-PT) and *knowledge-leveraged prototype matching* (KL-PM) are first introduced as the bases. Applying them, the *knowledge-leveraged transfer fuzzy C-means* (KL-TFCM) method and its three-stage-interlinked framework, including knowledge extraction, knowledge matching, and knowledge utilization, are developed. There are two specific versions: KL-TFCM-c and KL-TFCM-f, i.e. the so-called crisp and flexible forms, which use the strategies of maximum matching degree and weighted sum, respectively. The significance of our work is fourfold: 1) Owing to the adjustability of referable degree between the source and target domains, KL-PT is capable of appropriately learning the insightful knowledge, i.e. the cluster prototypes, from the source domain; 2) KL-PM is able to self-adaptively determine the reasonable pairwise relationships of cluster prototypes between the source and target domains, even if the numbers of clusters differ in the two domains; 3) The joint action of KL-PM and KL-PT can effectively resolve the data inconsistency and heterogeneity between the source and target domains, e.g. the data distribution diversity and cluster number difference. Thus, using the three-stage-based knowledge transfer, the beneficial knowledge from the source domain can be extensively, self-adaptively leveraged in the target domain. As evidence of this, both KL-TFCM-c and KL-TFCM-f surpass many existing clustering methods in texture image segmentation; and 4) In the case of different cluster numbers between the source and target domains, KL-TFCM-f proves higher clustering effectiveness and segmentation performance than does KL-TFCM-c.

1. Introduction

The effectiveness of clustering methods is often largely influenced by noise existing in target data sets. Usually, the greater the noise amplitude, the more negative the impact is. However, noise is nearly unavoidable and particularly impacts image segmentation [1–5], which motivates our research. Specifically, we address the issue that the segmentation performance of classic fuzzy *C*-means (FCM) [6–8], one of the most popular clustering approaches, is highly degraded by noise. While there have been numerous attempts to address this challenge, such as Ref. [1,2,9–15], most have not transcended the scope of traditional learning modalities and cannot achieve the required performance. In contrast, transfer learning [16,17], a state-of-the-art machine learning technique which will be introduced in the next section, has triggered an increasing amount of research interest owing to its distinctive advantages [18–42]. In brief, transfer learning helps one algorithm to improve the processing efficacy in the target domain, e.g. the image to be segmented, through the use of information in the source domain, e.g. another referenced image [16,22].

We pursue transfer learning as a means to improve the segmentation performance of FCM on target texture images in this manuscript. Specifically, the *knowledge-leveraged prototype transfer* (KL-PT) mechanism is introduced in response to the questions "What in the source domain can be enlisted as the knowledge?" and "How is such knowledge properly learned in the target domain?". Further, to the challenge of performing knowledge transfer when the numbers of clusters in the source and target domains are inconsistent, the *knowledge-leveraged prototype matching* (KL-PM) mechanism is presented based on FCM. After that, via these

* Corresponding author.
E-mail addresses: qianpjiang@jiangnan.edu.cn (P. Qian), jyz0512@163.com (Y. Jiang).

http://dx.doi.org/10.1016/j.knosys.2017.05.018

two mechanisms, and with a three-stage-interlinked framework, i.e. knowledge extraction, knowledge matching, and knowledge utilization, the *knowledge-leveraged transfer fuzzy C-means* (KL-TFCM) approach is developed for the purpose of target texture image segmentation. In addition, by means of the strategies of maximum matching degree and weighted sum, KL-TFCM is differentiated into two specific versions: KL-TFCM-c and KL-TFCM-f, i.e. the crisp and flexible forms of the KL-TFCM, respectively. In summary, the contributions of our efforts are as follows:

(1) KL-PT is devoted to leveraging the insightful knowledge, i.e., the cluster prototypes, of the source domain to guide the fuzzy clustering in the target domain, with the desirable adjustability of the referable degree between the source and target domains.
(2) KL-PM strives to self-adaptively determine the pairwise relationships with regard to the cluster prototypes between the source and target domains, particularly when the numbers of clusters in the two domains are inconsistent.
(3) By organically incorporating the strength of FCM, KL-PM, and KL-PT, and using the delicate three-stage-interlinked framework of knowledge transfer, we develop two versions of KL-TFCM methods, i.e., KL-TFCM-c and KL-TFCM-f, for the effective segmentation on target texture images. Both of them strive to properly leverage knowledge across domains, even though there is a certain extent of data inconsistency/heterogeneity between the source and target domains, e.g. the data distribution diversity and cluster number difference.
(4) Benefiting from the more flexible strategy to generate cluster representatives from the source domain, compared with KL-TFCM-c, KL-TFCM-f exhibits better noise-tolerance as well as clustering effectiveness, particularly when the numbers of clusters differ in the source and target domains; this facilitates its generally preferable segmentation performance on target texture images.

Moreover, for knowledge-leveraged transfer clustering, our proposed KL-PT and KL-PM mechanisms are also suitable for other classic fuzzy clustering models, e.g., maximum entropy clustering (MEC) [43,44], fuzzy clustering by quadratic regularization (FC-QR) [43,45], and possibilistic *C*-means (PCM) [43,46]; this additionally highlights our efforts in this manuscript.

The reminder in this manuscript is organized as follows. Section II reviews the theories and methods related to our research. Section III introduces, step-by-step, the knowledge transfer mechanisms regarding KL-PT and KL-PM, the KL-TFCM framework, and the two specific algorithms—KL-TFCM-c and KL-TFCM-f. Section IV evaluates the performance of KL-TFCM in texture image segmentation. Section V concludes and indicates areas of future work.

2. Related work

First, to facilitate understanding, common notations used throughout this paper are listed in Table 1.

2.1. Classic FCM

FCM attempts to group a set of given data instances, $X = \{\mathbf{x}_1, \ldots \mathbf{x}_N\} \in R^{N\times D}$, into C disjoint clusters by means of the membership matrix $\mathbf{U} = [\mu_{ij}]_{C\times N}$ and the cluster prototypes $\mathbf{V} = [\mathbf{v}_1, \cdots, \mathbf{v}_C]^{\mathrm{T}}$. For this purpose, FCM adopts the following objective function:

$$\begin{aligned}&\min\left(J_{\mathrm{FCM}}(\mathbf{U},\mathbf{V}) = \sum_{i=1}^{C}\sum_{j=1}^{N}\mu_{ij}^{m}\left\|\mathbf{x}_j-\mathbf{v}_i\right\|^2\right)\\ &\text{s.t.}\quad \mu_{ij}\in[0,1]\ \text{ and }\ \sum_{i=1}^{C}\mu_{ij}=1,\ \ j\in[1,N]\end{aligned} \tag{1}$$

where $m > 1$ is the fuzzifier, i.e. the weighting exponent that controls the fuzziness of partitions.

Via the Lagrange optimization, it is easy to derive the following updating rules for the cluster prototype $\mathbf{v}_i$ and membership degree μ_{ij}:

$$\mathbf{v}_i = \frac{\sum_{j=1}^{N}\mu_{ij}^{m}\mathbf{x}_j}{\sum_{j=1}^{N}\mu_{ij}^{m}} \tag{2}$$

$$\mu_{ij} = \frac{1}{\left[\sum_{k=1}^{C}\frac{\left\|\mathbf{x}_j-\mathbf{v}_i\right\|^2}{\left\|\mathbf{x}_j-\mathbf{v}_k\right\|^2}\right]^{\frac{1}{m-1}}} \tag{3}$$

Via the iterative procedure, the final fuzzy membership matrix $\mathbf{U}$ is attained, and then the cluster that each data instance should belong to can be determined in terms of the maximum probability principle.

As mentioned in Introduction, one disadvantage of FCM is its sensitivity to noise existing in target data sets which often incurs its inefficiency in target image segmentation.

2.2. Transfer learning based clustering and related methods

A. Transfer learning

Transfer learning [16–42] has recently become one of the hot topics in pattern recognition. Transfer learning focuses on improving the learning performance of intelligent algorithms on the target data set, i.e. the target domain, by referring to some beneficial information from the related data set, i.e. the source domain. Transfer learning is suitable for the situation where the target data are insufficient or distorted by noise or outliers, whereas some beneficial information from relevant data sets is available. Although the most common form of transfer learning entails only one source domain and one target domain, the number of source domains can be selected as needed.

The referable information between the source and target domains generally exhibits two types—*raw data* and *knowledge*. Due to the correlation between domains, some data in the source domain are certainly available supplements for those in the target domain. This is termed instance-transfer [16,33,34] in transfer learning. However, because of the difference of data distributions across domains, not all raw data in the source domain are beneficial to the target domain. To avoid the negative transfer [16,17,35], i.e. the phenomenon that source domain data or tasks contribute to the reduced performance of learning in the target domain, extracting knowledge instead of raw data from the source domain is a safe choose. In transfer learning, knowledge is referred to as a category of advanced information from the source domain, such as feature representations [16,17,25,36,37], parameters [16,21,39], and relationships [16,38], which is usually obtained from certain specific perspectives and via some reliable theories and precise procedures. Compared with raw data, knowledge is usually regarded as being more insightful as well as possessing stronger anti-noise capability. In some cases where the original data in the source domain are not accessible, for instance, because of privacy protection, it could be the only feasible pathway for transfer learning to extract knowledge rather than raw data from the source domain.

In general, there have been three categories of transfer learning [16,17] so far, i.e. inductive transfer learning, transductive transfer learning, and unsupervised transfer learning. In inductive transfer learning, it is required to induce an objective predictive model based on the labeled data in the target domain and with the assistance of the data or knowledge from the source domain. Many