Future Generation Computer Systems 82 (2018) 119–126

Contents lists available at ScienceDirect

Future Generation Computer Systems

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

Using general master equation for feature fusion

Weimin Peng [a,*], Aihong Chen [b], Jing Chen [a]

[a] School of Computer Science and Technology, Hangzhou Dianzi University, Hangzhou 310018, China
[b] School of Life Information and Instrument Engineering, Hangzhou Dianzi University, Hangzhou 310018, China

HIGHLIGHTS

- The continuous interaction model using GME which is used to widen the differences of the fusion probabilities of feature samples.
- The duplicate detection method based on Wootters statistical distance.
- The feature fusion method using weighted median operation.

ARTICLE INFO

Article history:
Received 3 March 2017
Received in revised form 19 December 2017
Accepted 3 January 2018
Available online 8 January 2018

Keywords:
Gaussian function
General master equation
Duplicate detection
Feature fusion
Weighted median operation

ABSTRACT

The rational division of subsets is a key issue for feature fusion, which often requires that the feature data units in different subsets can be differentiated easily. Regarding this, this paper uses the transformation effect between microscopic and macroscopic of general master equation to widen the differences of fusion probability between the feature data units in different subsets. Then, based on the more differentiable feature data units with widened fusion probabilities, this paper proposes a new dynamic quantum inspired feature fusion method, which uses the Wootters statistical distance in probability space to detect the duplicate feature data and uses the weighted median operation to fuse the detected duplicate feature data. The experimental results show that the fusion performances on fusion rate, relative completeness, and conciseness of the proposed feature fusion method are encouraging.

1. Introduction

For the heterogeneous feature data after schema mapping, data redundancy is unavoidable, which will damage the effectiveness and efficiency of data processing. Regarding this, it is important to efficiently reduce data redundancy and obtain the single, consistent, and clean representation of the existing feature data through feature data fusion (abbreviated as "feature fusion"). So, the main task of feature fusion is to develop a set of duplicate detection and feature fusion models which can efficiently improve the completeness and conciseness of the existing feature data. And the key issue of this task is to differentiate the feature data units and divide the source dataset into different subsets based on the defined relationships between feature data units. Therefore, we should widen the differences between the feature data units in different subsets and narrow the differences between the feature data units in the same subset. The fusion result of the feature data units in a subset depends on the representations and attributes (e.g. fusion probabilities) of feature data units.

In general, it is not easy to define the differentiable relationships between the original feature data units. So, the static feature fusion methods, which use the feature data units' initial attributes to detect and fuse the duplicate feature data, require relatively more complicate duplicate detection and feature fusion models. Overall, the classical inference based methods, such as Bayesian inference [1,2], fuzzy inference [3], and neural network inference [4], and the classical estimation based methods, such as least squares [5], Kalman filter [6], and particle filter [7], are static feature fusion methods. Recently, the classical based fusion methods on different types of feature data, such as the multi-focus image fusion method using dense scale invariant feature transform [8], the multi-modal medical image fusion method using the inter-scale and intra-scale dependencies [9] and the edge preserved images fusion method using multi-scale toggle contrast operator [10], the classical based fusion methods used for other technical fields, such as the evidence-based fusion method used for 3D model search [11] and the motion blob based fusion method used for traffic scene surveillance [12], and the quantum inspired feature fusion method based on maximum von Neumann entropy [13] are also static fusion methods.

The dynamic feature fusion methods use the more differentiable attributes after interaction to detect and fuse the duplicate

* Corresponding author.
E-mail addresses: penwm@hdu.edu.cn (W. Peng), chenah@hdu.edu.cn (A. Chen), cj@hdu.edu.cn (J. Chen).

https://doi.org/10.1016/j.future.2018.01.006

feature data, and require relatively simpler duplicate detection and feature fusion models but additional interaction process. However, the already developed dynamic feature fusion method [14] just discusses the case where the interaction process is discrete and Markovian. That is to say, the interaction component between two feature data units at time t is determined by the one at time $t'(t' < t)$ only. But if the interaction process is continuous and non-Markovian, then a new interaction model is needed, which can govern the discrete and continuous processes. Generally, the continuous case can be sharpened into the discrete case, and the discrete case is just a special continuous case. Motivated by this, this paper focuses on two aspects: (1) establishing a general interaction model which is continuous and non-Markovian and can better differentiate the feature data units in different subsets; (2) developing the corresponding dynamic quantum inspired feature fusion method which can better improve the (relative) completeness and conciseness of the source dataset with relatively simpler detection and fusion models.

The general master equation (GME) is an entity one meets with on the wayside in one's journey from the microscopic to the macroscopic level of the dynamics of large systems in statistics mechanics [15]. Essentially, GME descripts the continuous transformation process from microscopic to macroscopic, and is consistent to the above presented continuous interaction process. Here, the microscopic level is the initial states of feature data units where the feature data units are discrete and are difficult to be differentiated. The macroscopic level is the final states of feature data units after interaction where the differences between the feature data units in different subsets are widened. So, it is reasonable to use GME for feature fusion. The contributions of this paper are the continuous interaction model governed by GME and the corresponding detection and fusion models, which have important implications to efficiently reduce data redundancy and obtain the concise representation of the existing feature data. Compared to the classical inference based and estimation based feature fusion methods, the static quantum inspired feature fusion methods [13,16], and the dynamic and discrete quantum inspired feature fusion method [14], the proposed feature fusion method is quantum inspired, dynamic, and continuous.

To establish the interaction model using GME, the key step is to define the transition function and the transition probability between feature data units. For the continuous interaction process, we take the Gaussian function instead of the δ function as the transition function because the Gaussian function is continuous and topological isomorphic compared to the δ function. Usually, the δ function is suitable for the discrete interaction process. As shown in Fig. 1, the Gaussian function is the expansion of the δ function where the indefinite integrations of these two functions must be equal to 1. On the contrary, the Gaussian function in Fig. 1 can be sharpened into the δ function. Certainly, besides the Gaussian function, more continuous transition functions, which are topological isomorphic with the δ function, can be studied in the future. The transition probability of a feature data unit is calculated according to the initial fusion probabilities of all feature data units and the transition function which directs the transition process of the resultant transition probabilities as a whole.

Due to the effect of quantum parallelization [17], the quantum inspired feature fusion methods, where the feature data units are represented as the basic quantum states, quantum phases, and density matrixes, have potential high efficiency. Here, inspired by the idea of lattice structure [17], we quantize feature data unit, i.e., feature samples, into basic quantum states. Then, using the quantum inner product operation, we calculate the linking weights between different quantized feature samples, and thus obtain the initial fusion probabilities of all feature samples. The subsequent fusion probabilities of feature samples at different collision and reaction steps can be deducted according to the continuous transition function. When the interaction steps reach the given threshold, the interaction process is completed and the differences of fusion probability between feature samples are widened. Based on the final fusion probabilities of feature samples, we calculate the Wootters statistical distances in probability space [16,18] between feature samples and take them as the basis of duplicate detection. Then, according to the standard deviation of Wootters statistical distance, the source dataset is divided into different subsets incrementally. All the quantized feature samples in a subset will be fused into a new object quantized feature sample using the weighted median operation for quantum bits (qubits). Fig. 2 shows the continuous feature fusion process using general maser equation.

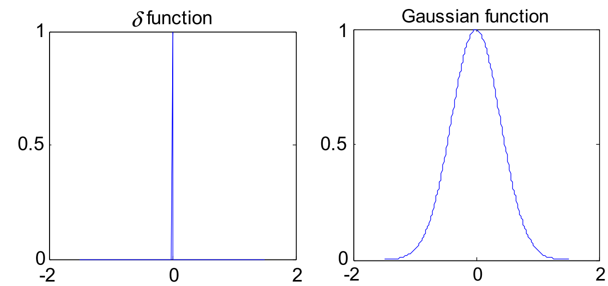

Fig. 1. Expanding the δ function into the Gaussian function.

In Section 2, the interaction model using GME is presented. Section 3 presents the duplicate detection models based on Wootters statistical distance and the feature fusion models using the weighted median operation. The related experimental results are shown in Section 4. The conclusions are drawn at the end of this paper.

2. Interaction model using GME

A feature dataset is defined as $X = [s_1, s_2, \ldots, s_i, \ldots, s_n]^T$ which contains n feature samples. The feature sample s_i is defined as $s_i = (x_i^1, x_i^2, \ldots, x_i^j, \ldots, x_i^L)$ $(x_i^j \in X^j)$, where the included feature elements $x_i^1, x_i^2, \ldots, x_i^j, \ldots, x_i^L$ are extracted from L different feature vectors $X^1, X^2, \ldots, X^j, \ldots, X^L$. The feature element x_i^j is quantized as the quantum state with M qubits, i.e., $|x_i^j\rangle = |b_{i,j}^1 \cdots b_{i,j}^k \cdots b_{i,j}^M\rangle$, where M is equal to the number of unique values in the feature elements' interval $[a, b]$. According to the position of x_i^j in the unique value sequence of $[a, b]$, the qubit $|b_{i,j}^k\rangle$ is equal to $|0\rangle$ or $|1\rangle$. So, m $(1 \le m \le M)$ possible values in the unique value sequence mean that m qubits of $|1\rangle$ locate in $|b_{i,j}^1 \cdots b_{i,j}^k \cdots b_{i,j}^M\rangle$, where, the indexes of the m values are equal to the ones of the m qubits. The quantum representation of the feature sample s_i is constituted by the quantum representations of the included feature elements and contains ML qubits, i.e., $|s_i\rangle = |b_{i,1}^1 \cdots b_{i,1}^M \cdots b_{i,j}^1 \cdots b_{i,j}^k \cdots b_{i,j}^M \cdots b_{i,L}^1 \cdots b_{i,L}^M\rangle$. Table 1 shows the definitions of the main notations in this paper.

Based on the quantum representations of feature samples, the linking weight between two quantized feature samples s_i and $s_{i'}$ is calculated according to the corresponding equivalent qubits between them and is equal to their inner product.

$$lw(s_i, s_{i'}) = \langle s_i | s_{i'} \rangle \tag{1}$$

The linking network (shown as Fig. 3) is constructed by the feature samples, which are taken as the linking nodes, and the linking weights between them. Based on the linking network, the migration probability from s_i to $s_{i'}$ is time-independent and is defined as the linking weight between s_i and $s_{i'}$ in relation to the linking