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Fast window fusion using fuzzy equivalence relation

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ABSTRACT

Current window fusion of the sliding window based human detection is rather slow. This paper proposes a fast fuzzy equivalence relation based method (FER). It merges candidate windows based on the fuzzy equivalence relation structured from the normal fuzzy similarity relation. Experimental results demonstrate that the method can merge candidate windows faster than the popular non-maximum suppression based method (NMS) and the bounding region method (BR), while maintaining the detection quality.

1. Introduction

Sliding window strategy has been widely adopted as the main method to detect candidate humans in pedestrian detection research (Enzweiler and Gavrila, 2009; Gerónimo et al., 2010). It slides a detection window to search the human with a human detector. Normally there will be many candidate windows obtained, therefore, a post-processing of fusing all candidate windows into the final detections is required. This paper studies this window fusion problem and proposes a new and fast fuzzy equivalence relation based method (FER).

There have been some studies on window fusion, such as the heuristic fusion method (Rowley et al., 1996), the bounding region method (BR) (Viola and Jones, 2001,Viola and Jones, 2004), the response based method (Schneiderman and Kanade, 2004) and the non-maximum suppression method (NMS) (Dalal, 2006). As far as we know, there still lacks of a proper method to measure their performances partially due to their dependences on the previous detection steps. But at least one feature of those method we can measure, fusion speed. In fact, some of them are faster than others, e.g., BR is faster than NMS. Speed may affect the whole detection performance especially in real-time scenario. Therefore it is worthwhile to propose a fast window fusion method without sacrificing the performance. To this end, we adopt the fuzzy set theory and propose the FER method based on the fuzzy equivalence relation. Our experiments show that this method can merge windows efficiently in a faster speed than NMS and BR.

In the following, the related studies are introduced in Section 2 with the related fuzzy set theories briefly reviewed in Section 3. Section 4 discusses the FER method in detail. The experimental results are presented in Section 5 and the whole paper is concluded in Section 6.

2. Related work

In this section, we first review fuzzy set and fuzzy clustering studies and then introduce the literatures on window fusion for sliding window based human detection.

2.1. Fuzzy set

Fuzzy set theory was proposed by Zadeh, 1965 as an extension of the classical notion of set. In the classical set theory, an element either belongs or does not belong to a set. In contrast to such a two-valued logic, fuzzy set theory permits an element to partially belong to a set, where the partiality is valued between 0 and 1. Since then, fuzzy set theory is studied intensively, e.g., (de Glas, 1983; Novák et al., 1999; Piegat, 2005; Rezaei et al., 2006; Mendel, 2007; Ruspini, 2012). Recently Zadeh, 2008 discussed the importance of fuzzy logic from the nontraditional perspective and explained its important features: graduation, granulation, precisiation and the concept of a generalized constraint. He concluded that fuzzy logic has a high precisiation power.

Fuzzy set theory has been widely applied to different domains for incomplete or imprecise information (Zimmerman, 2010), e.g., control, clustering, data mining, decision, optimization. We are interested in fuzzy clustering (Höppner et al., 1999; de Oliveira and Pedrycz, 2007) which classifies objects according to their membership levels. Especially the hierarchical clustering methods

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based on fuzzy equivalence relation (Klir et al., 1995; Delgado et al., 1996) are attractive for the window fusion purpose because they do not need specify the cluster numbers.

2.2. Fuzzy clustering

Perhaps the most popular fuzzy clustering method is fuzzy c-means (FCM) (Dunn, 1973; Bezdek, 1981). FCM clusters data by optimizing an objective function measuring the similarities between the data and their centers. There are some improvements of FCM in the literatures, e.g., the fuzzy possibilistic c-means model and algorithm (Pal et al., 2005), the generalized FCM method (Jian and Yang, 2005), the kernel-based FCM methods (Graves and Pedrycz, 2010) and the multiple kernel FCM method (Huang et al., 2012). The FCMs-based methods need pre-specified desired cluster numbers and, therefore, are inconvenient whenever the desired number can not be determined in advance.

The shortcoming of FCMs-based methods can be overcomed by the hierarchical clustering using fuzzy equivalence relation (Klir et al., 1995; Delgado et al., 1996). However, the original clustering methods requires evaluating an accurate fuzzy equivalence relation which is difficult to derive directly. Lee, 1999 proposed to use the transitive closure as the fuzzy equivalence relation, which is computed from the normal fuzzy similarity relation. This idea is popular although there are alternative methods (Mirzaei and Rahmati, 2010). Mirzaei and Rahmati, 2010 further presented an iterative procedure to combine hierarchically clustered results without mismatch based on combining dendrogram-description matrices. Their idea is also applied by Ciaramella et al., 2011 to simulate the atmospherical phenomena.

Some other researches can be utilized for efficient fuzzy clustering. For example, Lee, 2001 and De Meyer et al., 2004 proposed new algorithms for computing the transitive closure; Le Capitaine, 2012 and Rezaei et al., 2006 proposed new similarity measures.

Fuzzy clustering can be applied to various areas, including text mining (Deng et al., 2010), astronomical data mining (Sessa et al., 2002), document clustering (Miyamoto, 1539), image segmentation (Naz et al., 2010), image retrieval (Ooi and Lim, 2009), etc. More in-depth discussion on the recent development can be found in (de Oliveira and Pedrycz, 2007).

However, as far as we know, there is no study of applying fuzzy clustering to the window fusion. Window fusion is to merge candidate windows into final correct detection windows by clustering similar ones. Apparently, it also belongs to the clustering problem and can be solved by fuzzy clustering. Therefore, we study the application of fuzzy clustering to the window fusion. We believe some relatively simple techniques are enough for our purpose because the candidate windows for putative pedestrians are normally sparse. Specially, in our method, (1) the idea of hierarchical clustering using fuzzy equivalence relation for unspecified number of clusters is adopted and simplified to compute only one transitive closure, therefore, no clustering combination in previous researches is needed; and (2) the traditional matrix method (De Meyer et al., 2004; Mirzaei and Rahmati, 2010) is used to obtain the key component – the transitive closure, considering the relatively small size of the fuzzy similarity matrix.

2.3. Window fusion

Most existing studies on window fusion compare the properties of the candidate windows directly. Rowley et al., 1996 decided the real face window simply based on the number of candidate windows in the neighboring area. A face window is confirmed only when the number is bigger than a pre-defined threshold. Viola and Jones, 2001,Viola and Jones, 2004 partitioned the candidate windows into disjoint subsets and merged the windows into the same subset if their bounding regions overlap. Therefore we call it as bounding region method (BR). The final true windows of BR are computed by averaging all borders of the overlapping windows. Schneiderman and Kanade, 2004 obtained the true window by searching the highest response in the circular neighboring area.

These direct methods are generally simple, intuitive and easy to implement. For them, only one final window is obtained within the neighboring area when candidates are very close or partially overlapped. Therefore it is prone to misclassification. Different scales of candidates are not considered for better discrimination.

Recently Dalal, 2006 proposed a new method called non-maximum suppression (NMS). In this method, window fusion is taken to be a kernel density estimation problem and treated as a suppression of non-maximum responses. Each detection is depicted by a 3-D position and scale space, and the mean-shift mode seeking method is used to localize the final detection. This method can effectively detect targets appearing in different scales and thus reduce classification errors. Therefore non-maximum suppression has been widely used in human detection related research (Wang and Lien, 2007; Bourdev et al., 2010; Parikh and Lawrence Zitnick, 2011). But the major drawback is the high computation complexity due to the mean-shift based clustering.

To speed up the NMS without degrading the fusion performance, we propose the FER method, which is based on fuzzy equivalence relation. Our experiments show that FER is significantly faster than NMS and BR.

3. Review of related fuzzy set theories

In this section, we review some related basic fuzzy set theories: fuzzy set, fuzzy relation, fuzzy equivalence relation and α-cut. For more details on fuzzy set theory and its application, please refer to Zadeh, 1965, Klir et al., 1995 and Xu et al., 2007.

3.1. Fuzzy set

A set is a collection of objects and an object in the set is called an element. In the classical set theory, the element either belongs to (*true*) or does not belong to (*false*) the set.

However, a logic based on the two values, '*true*' and '*false*', is sometimes inadequate when describing human reasoning. Therefore Zadeh proposed the fuzzy set as an extension of the classical set. Every element x of a fuzzy set A has a varying degree of membership $\Phi_A(0 \leqslant \Phi_A(x) \leqslant 1)$ where the value 1 or 0 means x is fully included in A or not included in A.

The element of a classical set is either in the set with membership degree '1' or out of the set with membership degree '0'. Therefore, the classical set is a special case of the fuzzy set. The classical set operations can be extended to the fuzzy set and therefore a series of fuzzy set operations are available.

3.2. Fuzzy relation

In the classical set, the relationship between elements (classical relation) is only in two degrees: '*completed related*' (1) or '*not related*' (0). It is built on the Cartesian product which is defined as a n-tuple set for n sets $A_i(1 \leqslant i \leqslant n)$

$$A_1 \times A_2 \times \cdots \times A_n = \{(a_1, a_2, \ldots, a_n) | a_i \in A_i,\ i = 1, \ldots, n\}.$$

The classical relation is a subset of the Cartesian product, which has the basic set operations, including union, intersection, etc.

Fuzzy relation, on the other hand, takes on varying degrees of relationship between 1 and 0. Let $a_i(1 \leqslant i \leqslant n)$ represent the elements from A_i. Fuzzy relation R is the relation among elements of A_i and described by a membership function $\Phi_R(a_1, a_2, \ldots, a_n)$. The