


# A Discriminative Locality-Sensitive Dictionary Learning With Kernel Weighted KNN Classification for Video Semantic Concepts Analysis

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## ABSTRACT

Video semantic concept analysis has received a lot of research attention in the area of human computer interactions in recent times. Reconstruction error classification methods based on sparse coefficients do not consider discrimination, essential for classification performance between video samples. To further improve the accuracy of video semantic classification, a video semantic concept classification approach based on sparse coefficient vector (SCV) and a kernel-based weighted KNN (KWKNN) is proposed in this paper. In the proposed approach, a loss function that integrates reconstruction error and discrimination is put forward. The authors calculate the loss function value between the test sample and training samples from each class according to the loss function criterion, and then vote on statistical results. Finally, this paper modifies the vote results combined with the kernel weight coefficient of each class and determine the video semantic concept. The experimental results show that this method effectively improves the classification accuracy for video semantic analysis and shorten the time used in the semantic classification compared with some baseline approaches.

## KEYWORDS

Kernel Weighted KNN, Locality-Sensitive Adaptor, Structured Sparse Representation, Video Semantic Concept Analysis

## 1. INTRODUCTION

Video semantic content analysis is currently receiving a lot of research attention from the sports world, which is facilitating the work of sports experts, content providers and end users (Babu, Tom, & Wadekar, 2016; Jiang, 2016). The key concept of video semantic analysis is the exploitation of an effective mapping between the low-level visual features and the high-level semantic concepts from multimedia datasets, to efficiently extract the high-level semantic concepts from video data. Recently, video semantic analysis has become a blooming research area by many scholars and a significant progress has been made in the field in recent times (Deng, Hu, & Guo, 2012; Fu, Hu, Chen, & Ren, 2012; Huang, Shih, & Chao, 2006; Song, Shao, Yang, & Wu, 2017). For instance, a VSA approach based on fusion and interaction of multi-features and multi-models for sports semantic analysis

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was presented in (iaqi Fu, Hu, Chen, & Ren, 2012). This was done using a semantic color ratio that classified video shots arbitrarily into in-shots, global shots and out-shots for effective classification of sports video. In bridging the gap between low-level features and high-level semantic information, an ontology model based on semantic video object was proposed in (Liang, Xiangming, Bo, & Wei, 2010). A video semantics approach for events detection and weakly genre classification was also proposed in (You, Liu, & Perkis, 2010). This utilized the naïve Bayesian classifier and Hidden Markov Model (HMM) for video classification.

More so, the application of Sparse Representation (SR) with VSA is gaining significant attention both in academia and industry. This is due to the proliferation of more sophisticated gadgets coupled with the widespread use of social media in these contemporary times. The prospective applications of video data as already known, encompasses a wide array of domain and environments; from accessing the authoritative content that are concealed in deep web and databases to be decentralized on person to person applications. This is as a result of an increase in creation of digital contents, the need and potential retrieval of information stored in distributed sources across the web, has become more imperative and crucial. Frankly, experiments have shown that, SR approaches record good performance results in video analysis. In addition, semantic analysis and action recognitions are essential components of video semantic analysis (Zhan, Liu, Gou, & Wang, 2016b; J. Zheng, Jiang, & Chellappa, 2016). Discriminative dictionaries are learned in action recognitions with SR, which is applied to realize optimal classification accuracy and effective video action features (Grothe & Park, 2000; P. Wang, Li, Li, & Hou, 2018; Zhan et al., 2016b). A kernel discriminative sparse based approach was proposed in (Zhan, Dai, Mao, Liu, & Sheng, 2018) for video semantic feature representation with regards to VSA. By theory, sparse based approaches are able to tolerate signal interferences and are able to reconstruct signals with massive fidelity. The quality of the dictionary is therefore very essential in representing sparse coefficients for an effective classification results. However, prior SR-based approaches implemented for video analysis including but not limited to the ones discussed in (Bai, Li, & Zhou, 2015; Grothe & Park, 2000; Sun, Liu, Tang, & Tao, 2014; B. Wang, Wang, Xiao, Wang, & Zhang, 2012; P. Wang et al., 2018; Xu, Sun, Quan, & Zheng, 2015; Zha et al., 2018; Zhan et al., 2016b), are challenged with a number of representation and classification issues. Many of these methods are utilized in addressing issues bordering on their implementations with small data sizes and still images primarily, in dealing with linear systems (Wright, Yang, Ganesh, Sastry, & Ma, 2009). This premise has been extensively utilized in image recognition and detection systems realistically without much emphasis on the application of SR with nonlinear systems and VSA. Indeed, the fact is that, despite good classification results by these SR approaches, most prior systems do not fully exploit the discriminative local and non-linear information that could be hidden in the structure of videos, not to mention the inherent complexity and stability issues concerning the kernel based approaches (Dumitrescu & Irofti, 2018; Gao, Tsang, & Chia, 2013; Nweke, Ying, Al-Garadi, & Alo, 2018; Z. Wang, Wang, Liu, & Zhang, 2017; Wu, Li, Xu, Chen, & Yao, 2016; L. Zhang, Zhou, & Li, 2015). Furthermore, they could not exploit fully the discriminative information hidden in the training samples of video data due to the presence of noisy information in the original training sample, hence the need for a more pragmatic approach in addressing these issues to realize effective video classification results.

Presently, video classification approaches can be grouped into two (2) categories: Statistical-based and Rule-based approaches (Atmadja & Purwarianti, 2016). The Statistical-based approaches lean itself to annotate video clips integrated with classifiers and models in classifying other videos to obtain relevant information from video clips of known class labels, after which it discriminates video clips of unknown class labels. This method can be implemented on the grounds that, a large number of training samples of known class labels are required for an effective classification performance. On the contrary, the Rule-based methods are explicitly suitable for some specific domains. It uses domain-specific knowledge to detect and analyze semantic concepts contained in video. However, the approach is complex and time-consuming to establish classification rules for videos in certain

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