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WILD ANIMAL DETECTION USING MULTI-CLUSTER FEATURE SELECTION

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***Abstract*-** Wild animal detection helps wildlife researchers to analyze and study wild animal habitat and behavior. Discriminative Feature-oriented Dictionary Learning (DFDL) was utilized for learning discriminative features of positive images that have animals present in positive class, in addition of negative images that do not have animals present in that class. But, this approach has low performance for detection of visual wild animals. Hence, in this paper, Multi-Cluster Feature Selection (MCFS) is proposed for unsupervised feature selection and wild animal detection. Those features are chosen, which the multi-cluster structure of the data is well preserved. Based on spectral analysis approaches, the proposed method suggests a principled manner for calculating the correlations among various features without label information. Thus, the proposed technique handles the data with multiple cluster structure. The experimental results show that the proposed approach provides the better results.

***Keywords*:** Dictionary Learning, Multi-Cluster Feature Selection, Wild animal detection, Spectral analysis

I. INTRODUCTION

In the field of computer vision, object tracking and detection were used for decades. But, the entire techniques were contained restrictions using the particular circumstances. Moving object detection (Neff, M. G., et al. 2011) in stationary cameras and a constant background were handled easily. An amount of trackers were created based on various techniques, consists of state estimation techniques (Bhat, K. S., et al. 2000) and background modelling approaches (KaewTraKulPong, P., & Bowden, R. 2002). Considered the issue of moving object detection from moving cameras, a technique was the extension of background subtraction (Reilly, V., et al. 2010; Wang, Y., et al. 2012).

Wildlife researchers were analyzing and studying the wild animals and their behavior. Animal detection using sparse representation (Gupta, P., & Verma, G. K. 2017) was presented by DFDL. It was shown a low complexity approach and extracted discriminative class-specific features for detecting the animal. It was obtained class specific dictionaries allowed to represent a new image for discovering of the class of the image. These dictionaries were incapable of representing the samples of other classes. However, this technique has low performance for detection of visual wild animals.

In this paper, MCFS is proposed for unsupervised feature selection and wild animal detection. Those features are chosen such that the multi-cluster structure of the data is preserved. Using spectral analysis techniques, this approach is suggested a principled manner for computing the correlations among various features without label information. So, this approach is handled the data and multiple cluster structure. The corresponding optimization issue is integrated a L1-regularized least squares problem and a sparse eigen-problem, so it is solved.

The remainder of the article is organized as follows: Section 2 describes about the wild animal detection techniques. Section 3 describes about the proposed methods. Section 4 illustrates the performance evaluation of the proposed techniques. Section 5 concludes the research work.

II. RELATED WORK

An approach (Fang, Y., et al. 2016) was discussed for detecting an animal by taking benefit of global patterns of pixel motion. By applying a pixel velocity threshold, a coarse segmentation was removed most parts of the background. Based on the segmented regions, another threshold was utilized to filter out negative candidates. Scientists and ecologists (Nguyen, H., et al. 2017) were discussed for monitoring wildlife in an open environment. Leveraging on recent advances in deep learning approaches in computer vision, a framework was proposed to build automated animal recognition in the wild, aiming at an automated wildlife monitoring system. A single-labeled dataset was used from wildlife spotter project, completed by citizen scientists and the deep convolutional neural network

architectures, to train a computational system capable of filtering animal images and discover species automatically.
A five-component detection pipeline (Parham, J., et al. 2018) was proposed for animal recognition. This approach was obtained a collection of Annotations of Interest (AoI) with species and viewpoint labels. This technique was used for providing better ecological information to conservationists and maximizing the reliability and automation of animal censusing studies. A two-channeled perceiving residual pyramid networks (Zhu, C., et al. 2017) was developed for camera trap images objection. This approach was attended to generate high-resolution and high-quality results. For providing enough local information, depth cue was extracted from the original images and used two-channeled perceiving model as input to training the networks. The three-layer residual blocks were learned for merging the entire information and generated full size detection results.

Computer vision techniques (Zhang, T., et al. 2015) were investigated to assist in the study of kangaroos. A kangaroo image dataset was built from collected data for investigating the feasibility. Additionally, a multi-pose technique was designed using Deformable Part Model to obtain reasonable detection accuracy. A system capable of detecting different large sized wild animals (Jaskó, G., et al. 2013) was discussed from traffic scenes. Visual data was obtained from a camera with monocular color vision. The main goal was for analyzing the traffic scene image, to locate the regions of interest and to correctly classify them for discovering the animals that are on the road and might cause an accident. A saliency map was generated from the traffic scene image, based on intensity, color and orientation features. The salient regions of this map were assumed to be regions of interest.

III. PROPOSED METHODOLOGY

In this section, MCFS is described for unsupervised feature selection and wild animal detection. Those features are selected such that the multi-cluster structure of the data is well preserved. In addition, using spectral analysis techniques, this method suggests a principled manner for calculating the correlations between different features without label information. Then, this approach is handled the data with multiple cluster structure. The corresponding optimization issue incorporated L1-regularized least squares issue and a sparse eigen-issue, so it is solved.

3.1 Spectral Embedding for Cluster Analysis

Consider a group of points $X = [x_1, x_2, \dots, x_N], x_i \in R^M$, find a feature subset and size d, which is contained the most informative features. The points $\{x'_1, x'_2, \dots, x'_N\}$ denoted in the d-dimensional space R^d can be preserve the geometric structure as the data represented within the original M-dimentional space. As occurring data have multiple clusters structure, a good feature selection technique should consider the following two aspects:

- The selected features can be best preserve the cluster structure of the data
- The selected features can be covered the entire possible clusters within the data. As various features are contained different power on differentiating various clusters, it is undesirable which all the select features are differentiate cluster 1 and 2, however failed on differentiating cluster 1 and 3

MCFS algorithm is proposed for wild animal detection that assumes the above two aspects. To detect the cluster structure of data, spectral clustering (SC) techniques received important interests. The SC clusters the data points by the top eigenvectors of graph Laplacian. It is described on the affinity matrix of data points. SC is tried for discovering the best cut of the graph from the graph partitioning perspective thus the predefined criterion function were optimized. A lot of criterion functions are utilized along with the corresponding eigen-issues to discover their best solutions.

SC is a close connection and the studies on manifold learning (ML) that assume the case once the data can be drawn from sampling a probability distribution. It is supported on or near for a sub-manifold of the ambient space. A lot of ML techniques were used for detecting the underlying manifold structure. These techniques has been constructed a nearest neighbor graph for performing spectral analysis on the graph weight matrix and modeling the local geometric structure. These ML techniques are unfold the data manifold and provided the flat embedding for the data points. The SC is thought as a two-phase technique. Initial phase is unfolding the data manifold by the ML techniques and another phase is executing traditional clustering on the flat embedding to the data points.

Consider a graph and N vertices where each vertex corresponds to a data point. For each data point x_i, we find its p nearest neighbors and put an edge between x_i and its neighbors. There are a lot of choices to define the weight matrix W on the graph.
0-1 weighting: $W_{ij} = 1$ if and only if nodes $i\ and\ j$ can be connected through an edge. It is easy to measure.
Heat kernel (HK) weighting: If nodes $i\ and\ j$ can be connected,

$$W_{ij} = e^{-\frac{\|x_i - x_j\|^2}{\sigma}} \quad (1)$$

HK is an intrinsic connection to the Laplace Beltrami operator on differentiable functions on a manifold.
Dot-product (DP) weighting: If nodes $i\ and\ j$ can be connected,

$$W_{ij} = x_i^T x_j$$

(2)

If x is normalized for having unit norm, the dot product of two vectors is equivalent to the cosine similarity of the two vectors.

If the HK or DP weighting is used, a complete graph is utilized rather than the p-nearest neighbor's graph. Consider a diagonal matrix D whose entries can column sums of $W, D_{ii} = \sum_j W_{ij}$, the graph Laplacian is calculated $L = D - W$. The flat embedding for the data points, which unfold the data manifold are found via solving the below generalized eigen-issue,

$$Ly = \lambda Dy$$

(3)

$Y = [y_1, \dots, y_k], y_k$ indicates the eigenvectors of the above generalized eigen-issue with respect to the smallest eigen-value. Each row of Y denotes the flat embedding to each data point. The K is the intrinsic dimensionality of the data and each y_k reflects the data distribution along the corresponding dimension. Each y_k is reflect the data distribution on the corresponding cluster when one tries to execute cluster analysis of the data. Thus, if the cluster number of the data is known, the K is group to be equal to the number of clusters.

3.2 Learning Sparse Coefficient Vectors

The flat embedding Y is achieved for the data points, the significance of each feature with every intrinsic dimension is measured, in the same way, the contribution of every feature to differentiate every cluster.

a_k, a column of Y, a relevant subset of features can be found by reducing the fitting error,

$$\min_{a_k} \|y_k - X^T a_k\|^2 + \beta |a_k|$$

(4)

In the above equation, a_k indicates a M-dimensional vector and $|a_k| = \sum_{j=1}^{M} |a_{k,j}|$ represents the L1-norm of a_k. a_k essentially contains the combination coefficients for different features in approximating y_k. A few coefficients will be shrunk to exact zero if β is huge enough due to the nature of the L1-noem penalty. A subset containing the most relevant features are selected with respect to y_k.

The above equation is a regression issue. This L1-regularized regression issue is named as LASSO. The regression issue in the above equation has the following the same formulation,

$$\min_{a_k} \|y_k - X^T a_k\|^2$$

(5)

$$s.t. \quad |a_k| \le \gamma$$

The Least Angel Regression (LARs) technique is utilized to solve the optimization issue in the above equation. Rather than setting the parameter γ, this technique is provided another choice for controlling the sparseness of a_k via identifying the cardinality of a_k which is particularly convenient to the feature selection. It is possible that a few features are correlated. The combination of numerous weak features is better differentiating various clusters. Numerous supervised feature selection techniques are developed for considering this problem. Thus, the L1-regularized regression model to identify the subset of features rather than evaluating the contribution of each feature independently is clear.

3.3 Feature Selection on Sparse Coefficient Vectors

Selecting d features are considered from the M feature candidates. The technique investigated in the previous subsections is used for a data set containing K clusters to measure K sparse coefficient vectors $\{a_k\}_{k=1}^{K} \in R^M$.

The cardinality of every a_k is d and every entry in a_k corresponds to a feature. If the entire features are selected, which is contained at least one non-zero coefficient in K vectors $\{a_k\}_{k=1}^{K}$, it is possible that we will obtain more than d features. The following simple yet effective approach is used for selecting to select exactly d features from the K sparse coefficient vectors. For every feature j, the proposed approach score is defined to the feature,

$$MCFS(j) = \max_k |a_{k,j}|$$

(6)

In the above equation, $a_{k,j}$ denotes the $j-th$ element of vector a_k. Then, the entire features are sorted along with their MCFS scores in descending order and the top d features are selected.

3.4 Computational Complexity Analysis

The computational cost for every step are calculated as follows,

- The p-nearest neighbor graph construction phase requires $O(N^2M)$ to measure the pair wise distances and $O(N^2p)$ to discover p neighbors for every data point.
- Every row of the weight matrix W is contained approximate p non-zero values for a p-nearest neighbor graph. Lanczos mechanism is used to calculate the top K eigen-vectors of eigen-problem in the equation (1) within $O(K\, N_p)$ time.
- The LARs technique is solve the L1-regularize regression issue in equation (3) and cardinality constraint $(cardi(a_k) = d)$ in $O\,(d^3 + N\,d^2)$. Thus, $O(K\,d^3 + N\,Kd^2)$ required to solve the K regression issues in total.
- The MCFS scores for the entire features are measured within $O(K\,M)$.
- The top d features are found in $O(M \log M)^2$.

$K \ll N$ *and* p is fixed as a constant 5, the total cost for the proposed MCFS algorithm is,

$$O(N^2M + Kd^3 + N\,Kd^2 + M\log M) \quad (7)$$

Algorithm: the proposed MCFS for feature section

Input: N data points with M features; number of clusters K; number of selected features d; number of nearest neighbors p; the weighting technique (the parameter σ if choosing for using the HK weighting),

Output: d selected features

1. Construct a p nearest neighbor graph as discussed
2. Solve the generalized eigen-issue in Equation (3), Let $Y = [y_1, \cdots, y_K]$ have the top K eigenvectors with respect to the smallest eigen-values.
3. Solve K L1-regularized regression issues in Equation (5) using LARs mechanism with the cardinality constraint set to d. We get K sparse coefficient vectors $\{a_k\}_{k=1}^{K} \in R^M$.
4. Measure the MCFS score for every feature according to Equation (6).
5. return the top d features according to their MCFS scores.

IV. EXPERIMENTAL RESULTS

In this section, the performance of the proposed approach is analyzed with the existing techniques. The comparison is made between proposed MCFS and existing techniques in terms of true positive rate, recall, F-measure and accuracy.

4.1 True Positive Rate (TPR)

It is described as the ratio of number of correctly identified positive images to a total number of positive images.

$$TPR = \frac{T_P}{T_P + F_P}$$

In the above equation, T_P denotes true positive and F_P indicates false positive.

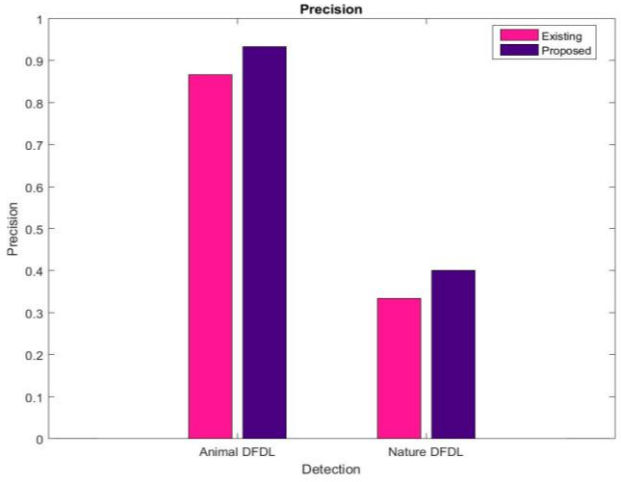

Figure 1. Comparison of True positive rate

Figure 1 shows that the comparison of proposed and existing techniques in terms of true positive rate. From this graph, detection level is represented in X-axis and true positive rate values are denoted in Y-axis. In this analysis, the TPR value is increased for proposed approach compared to existing approach.

4.2 Recall

It is evaluated according to the feature classification at true positive prediction, false negative. It is computed as follows,

$$Recall = \frac{T_P}{T_P + F_N}$$

In the above equation, F_N denotes false negative.

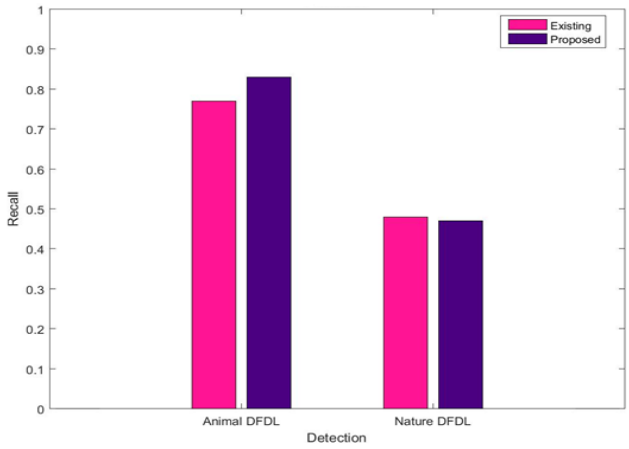

Figure 2. Comparison of Recall

Figure 2 shows that the comparison of proposed and existing approaches in terms of recall. In this graph, detection level is denoted in X-axis and recall values are represented in Y-axis. From this analysis, the recall value is decreased for proposed technique compared to the existing technique.

4.3 F-measure

It is computed from the precision and recall value. Then, it is calculated as,

$$F - measure = 2 \times \left(\frac{precision \times recall}{precision + recall}\right)$$

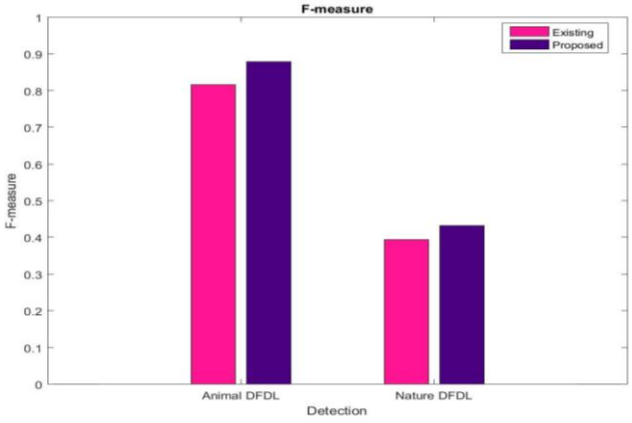

Figure 3. Comparison of F-measure

Figure 3 shows that the comparison of proposed and existing techniques in terms of F-measure. In this analysis, detection level is represented in X-axis and F-measure value is denoted in Y-axis. From this graph, the F-measure value is increased for proposed approach compared to the existing approach.

4.4 Accuracy

It is explained as the ratio of total number of images that were correctly detected by the system.

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N}$$

In the above equation, T_P denotes the number of positive images in that animal is detected, F_N represents the number of positive images in that animal is not detected, F_P denotes the number of negative images in that system wrongly detects animal and T_N represents the number of negative images in that system does not detect animal.

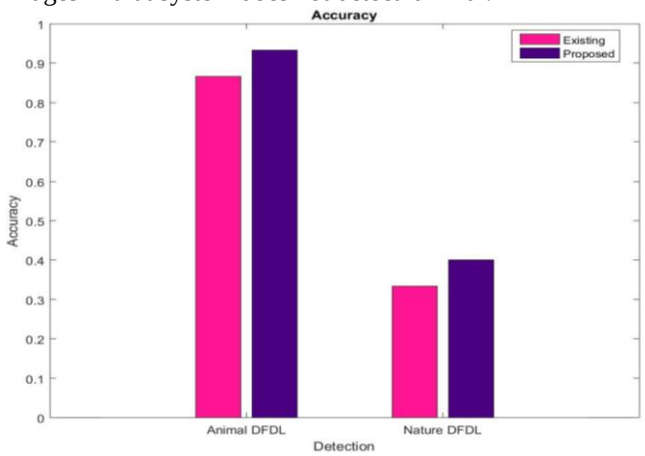

Figure 4. Comparison of Accuracy

Figure 4 shows that the comparison of proposed and existing techniques in terms of accuracy. In this graph, detection level is denoted in X-axis and accuracy values are represented in Y-axis. From this analysis, the accuracy value is increased for proposed technique compared to the existing technique.

V. CONCLUSION

In this work, MCFS is proposed for wild animal detection and unsupervised feature selection. Those features are selected such that the multi-cluster structure of the data is well preserved. Based on spectral analysis approaches, this method suggests a principled manner for calculating the correlations among various features without label information. So, this approach is well handled the data with multiple cluster structure. The corresponding optimization issue is involved a L1-regularized least squares problem and a sparse eigen-problem, thus it is efficiently solved. The experimental results show that the proposed MCFS technique provides better results in terms of true positive rate, recall, F-measure and accuracy.

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