

A LITERATURE SURVEY ON WILD ANIMAL DETECTION USING VARIOUS DATAMINING TECHNIQUES

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ABSTRACT

Now a days, world has made computers an inseparable part of their life as computers are used for performing the entire work of humans with better accuracy and efficiency. Visual scene analysis is a high-level tasks that acquire knowledge from videos or digital images that comes under the domain of computer vision. Object Detection is a field of computer vision and image processing which involves detecting objects of varying class (animal, humans or cars) present in images and videos. Some well-researched applications of object detection are in the domain of car detection, face detection, image retrieval and video surveillance. This survey especially focuses on to examine the different images and videos based object detection methods to support various environments. The main objective of this research is to study about different images and videos based object detection methods used for detecting and solving images and videos based object detection problems. This paper provides detailed information about the different object detection techniques in various environments. Finally, comparisons are made for different object detection methods used in different images and videos environments.

Keywords: Negative image , positive image

I INTRODUCTION

One of the tasks is analysis and interpretation of visual scenes by computers. Visual scene analysis is a high-level tasks that acquire knowledge from videos or digital images, which comes under the domain of computer vision. Computer vision deals with image data (such as digital images, a sequence of images, multi-view images, etc.) and information to form decisions.

Detection of objects from different scenes is a prime requirement for various computer vision applications. Human visual system is one such example which can easily detect and recognize one class of object from another class of object. Object detection is widely used for automatic analysis of digital data, Human-Computer Interaction (HCI), automated processes, smart vehicles and wild animal detection. Among different researches, applications of object detection are in the domain of car detection, face detection, image retrieval and video surveillance. The main contribution of this paper is for analyzing the different object detection methods in various environments.

The rest of the paper is planned as follows: Section 2 explains the different object detection methods used for various environments. Section 3 presents the comparison of the techniques in literature. Section 4 presents conclusion of this survey.

II LITERATURE SURVEY

Fang, Y., et al. [1] discussed a technique to move animal detection by taking benefit of global patterns of pixel motion. In the dataset, where animals make obvious movement against the background, motion vectors of every pixel were estimated by applying optical flow techniques. A coarse segmentation then eliminates most parts of the background via applying a pixel velocity threshold. Using the segmented regions, another threshold was used to filter out negative candidates, which could belong to the background.

Jaskó, G., et al. [2] presented a system capable of detecting different huge sized wild animals from traffic scenes. Visual data was obtained from a camera with monocular color vision. The objective was to analyze the traffic scene image, to locate the regions of interest and to correctly classify them for discovering the animals that were on the road and might cause an accident. A saliency map was generated from the traffic scene image using intensity, color and orientation features. The salient regions of this map were assumed to be regions of interest. A database was compiled from a large number of images containing various four-legged

wild animals. Relevant features were extracted from these and were utilized for training Support Vector Machine (SVM) classifiers.

Nguyen, H., et al. [3] investigated a main obstacle to scientists and ecologists to monitor wildlife in an open environment. Leveraging on recent advances in deep learning approaches in computer vision, a framework was introduced to build automated animal recognition in the wild, aiming at an automated wildlife monitoring system.

Parham, J., et al. [4] proposed a 5-component detection pipeline to utilize in a computer vision-based animal recognition system. The result of this approach was a collection of novel annotations of interest (AoI) with species and viewpoint labels. The concept of this approach was to increase the reliability and automation of animal censusing studies and to offer better ecological information to conservationists.

Matuska, S., et al. [5] discussed a new approach for object recognition by using hybrid local descriptors. This approach was utilized a combination of a few techniques (SIFT - Scale-invariant feature transform, SURF - Speeded Up Robust Features) and consists of second parts. The applicability of the presented hybrid techniques were demonstrated on a few images from dataset. Dataset classes represent big animals situated in Slovak country, namely wolf, fox, brown bear, deer and wild boar.

Xue, W., et al. [6] utilized a wireless sensor network based on UWB technology for deploying intrusion detection. By analyzing the characteristics of Ultra-wide band (UWB) signals, convolutional neural network (CNN) was employed for learning the characteristics of UWB signals automatically. The SVM or Softmax classifier was utilized for classifying human beings from animals.

Zhu, C., et al. [7] introduced a two-channeled perceiving residual pyramid networks towards automatic wild animal detection in low quality camera-trap images. This paper was extracted depth cue from the original images and used two-channeled perceiving model as input to training a networks. The three-layer residual blocks were used for merging the entire information and generating full size detection results. In addition, a novel high quality dataset with the complex wild environment was built using dataset design principles.

Zhang, T., et al. [8] focused on using computer vision approaches for assisting in the study of kangaroos in the wild. For investigating the feasibility, a kangaroo image dataset was built from collected data from several national parks across the State of Queensland. For achieving reasonable detection accuracy, a multi-pose approach was explored and a framework was proposed using the state-of-the-art Deformable Part Model (DPM).

Villa, A. G., et al. [9] stated the main problems inherent to camera trapping images automatic species identification. Through numerous experiments the capacity of very deep convolutional neural networks for automatizing species classification in camera-trap images was proved. Unbalanced, balanced, foreground objects selection and segmented versions of Snapshot Serengeti dataset were utilized for studying how a powerful learning algorithm performs in presence of four of the main problems inherent to camera trapping acquired data: unbalanced samples, empty frames, incomplete animal images and objects too far from focal distance.

Xue, C., et al. [10] developed a pair of universal primers for simultaneous detection of eight animal species, with a PCR assay. The new approach was shown to be specific, sensitive and reliable in the simultaneous identification of goat, sheep, deer, buffalo, cattle, yak, pig, and camel species. This technique was relatively simple and rapid, not requiring expensive equipment. The developed technique was represented a practical approach for routine analysis of meat samples, for determining fraudulent and mislabeled substitutions in meat products.

Kumar, S., & Singh, S. K. [11] proposed a low-cost system to monitor of pet animals (dogs) using their primary animal biometric identifiers. The recognition technique was utilized the one-shot similarity and distance metric based learning approaches to match and classify the extracted features of face images for recognition of pet animals (dog). A prototype was developed to evaluate the accuracy of the recognition system.

Lo, N. W., et al. [12] designed an enhanced approach that was monitored the distance among two mating objects and more effectively detects the mating behavior. Additionally, a more detailed portrayal of the mating behavior was further elaborated as a function of the distance patterns in the tails of two caged mice.

Pun, C. M., & Huang, G. [13] discussed a new on-line video segmentation approach. In this approach, after a superpixel generation procedure, each superpixel was represented through a new illumination-invariant color-texture-based superpixel feature. A new marker prediction algorithm was applied for predicting the marker superpixels in each frame. After the markers were predicted, video segmentation was executed as a region-merging-based interactive image segmentation procedure in each frame.

Zhou, L., & Zhang, Z. [14] presented a new segmentation and extraction technique using motion blur features. The blur features were extracted by using contourlet transform and considered as the prior information. An energy function was introduced to

extract the moving object from the original images. Considering that there exists some noise in segmented images, some morphological approaches were proposed for removing the noise.

Kleinnijenhuis, A. J., et al. [15] investigated a selective bottom-up Liquid Chromatography coupled to Mass Spectrometry (LC-MS) approach for quantitative gelatin species determination and a lower limit of quantification of 0.05%. It was defined the validation of this approach that was executed according to Good Laboratory Practice, and the theoretical justification for bovine and porcine target selection. The validated method was utilized for determining the purity of gelatin batches with regard to bovine and porcine constituents.

Besteiro, R., et al. [16] evaluated the agreement among two animal activity measurement techniques: a Passive infrared (PIR) detector that was used the sensor's digital signal for executing measurements and human observations of activity in a group of 50 weaned piglets on a commercial farm. The location chosen for the sensor allowed for the recording of the main transverse movements with respect to the orientation of the sensor that maximized its detection capacity. Human observation revealed two kinds of behavioral activity, feeding (eating or drinking) and playing. Additionally, animal weight affected the quality of measurements that decreased with the increase in the ratio among kg of live weight and area covered by the sensor. The kind of activity affected the precision of PIR detectors that better detected playing activities that were more intense than feeding activities.

Ferryman, J., et al. [17] discussed a video surveillance method which robustly and efficiently detects abandoned objects in surveillance scenes. This method was using a new threat assessment algorithm that was integrated the concept of ownership with automatic understanding of social relations to infer abandonment of objects. Implementation was achieved through development of a logic-based inference engine based on Prolog. Threat detection performance was conducted by testing against a range of datasets describing realistic situations and demonstrates a reduction in the number of false alarms generated.

Tarrit, K., et al. [18] presented a three-stage method for accurately detecting the main lines and vanishing points (VPs) in low-resolution images acquired through visual surveillance systems in indoor and outdoor railway platform environments. Initially, several frames were utilized for increasing the resolving power through a multi-frame image enhancer. Then, adaptive edge detection was performed and a new line clustering algorithm was applied for determining the parameters of the lines that converge at VPs; this was using statistics of the detected lines and heuristics about the type of scene. Finally, vanishing points were computed via a voting system to optimize detection in an attempt to omit spurious lines.

Rey, N., et al. [19] investigated a semi-automatic system able for detecting large mammals in semi-arid Savanna. It relies on an animal-detection system using machine learning, trained with crowd-sourced annotations provided by volunteers who manually interpreted sub-decimeter resolution color images. The system was achieved a high recall rate and a human operator can then remove false detections with limited effort. The system was provided good perspectives for the development of data-driven management practices in wildlife conservation.

Gupta, P., & Verma, G. K. [20] proposed a technique for detection of visual wild animals in images by dictionary learning. Discriminative Feature-oriented Dictionary Learning was utilized for learning discriminative features of positive images, that have animals present in positive class, in addition to of negative images that do not have animals present in that class. The system was created dictionaries that were class-specific and was capable of automatic feature extraction by example training image samples. The proposed approach was learned these dictionaries through positive (animal class and negative background class) sparse representation of image samples.

III COMPARISON OF VARIOUS IMAGES AND VIDEOS BASED OBJECT DETECTION TECHNIQUES

This section provides an overview of advantages and disadvantages in various images and videos based object detection techniques in different environments.

Table 3.1 Comparison of different images and videos based object detection techniques

Ref No	Title	Attributes (species)	Merits	Demerits	Performance metrics
[1]	Motion Based Animal Detection in Aerial Videos	zebras and antelope	Global pixel motion difference between the animal and the background.	In this approach, more effective local threshold selection methods are not used	Species = zebras False positive = 2.03% False Negative = 11.39%
[2]	Animal Detection from Traffic Scenarios Based	Based on SVM classifier, test number is 1 to 10	Highly accurate classifier	The static size of region delimiter box	Test number = 6 True positive (left facing animal) = 95%

	on Monocular Color Vision				True positive (right facing animal) = 90% True negative (Regions with no animals) = 90%
[3]	Animal Recognition and Identification with Deep Convolutional Neural Networks for Automated Wildlife Monitoring	Bird, Rat, Bandicoot, Rabbit, Mouse, Cat etc.	Robust, stable and suitable for dealing with images captured from the wild	Low accuracy	Six most common species Training 80% images Validation 20% images Model = Lite AlexNet Accuracy = 82.49% F-measure = 81.40%
[4]	An Animal Detection Pipeline for Identification	Masai Giraffe, Reticulated Giraffe, Sea Turtle, Whale Fluke, Grevy's Zebra, Plains Zebra	This approach is provided better ecological information to conservationists	Low accuracy	Accuracy = 72.75%
[5]	Classification of Wild Animals Based on SVM and Local Descriptors	Wild boar, brown bear, wolf, fox and deer	Promising results comparable with other key point detectors	Poor results with success rate of classification around 50% only	Classification success rate = 86%
[6]	Animal Intrusion Detection Based on Convolutional Neural Network	Null, Human and Animal	Improve the accuracy of detection	Low accuracy of animal detection	1) CNN + SVM Null = 100% Human being = 100% Animal = 96.5% 2) CNN + SoftMax Null = 100% Human being = 100% Animal = 97.75%
[7]	Towards Automatic Wild Animal Detection in Low Quality Camera-trap Images Using Two-channel Perceiving Residual Pyramid Networks	VWM dataset	Improves the quality of wild animal detection and more robustness	Low F-measure value	Mean Absolute Error = 0.0722 F-measure = 0.7303
[8]	Detecting Kangaroos In The Wild: The First Step Towards Automated Animal Surveillance	Kangaroo dataset	Reasonable detection accuracy	Low precision	True positive rate = 68.8% False positive rate = 0.3% Average precision = 84.25%
[9]	Towards Automatic Wild Animal Monitoring: Identification of Animal Species in Camera-trap Images using Very Deep Convolutional Neural Networks	Snapshot Serengeti dataset	High performance in classification	Poor illumination	Species = Grant's Gazelle Citizen Science Accuracy = 82.1% ConvNet Accuracy = 65.0%
[10]	Development and	goat, sheep, deer,	Simple and	-	The PCR products generated

	validation of a universal primer pair for the simultaneous detection of eight animal species	buffalo, cattle, yak, pig, and camel	rapid method		512 bp for buffalo
[11]	Monitoring of pet animal in smart cities using animal biometrics	Pet animal (dogs)	Improve the recognition accuracy	Does not used the real data of pet animals	Recognition rate = 96.87%
[12]	Caged mice mating behavior detection in surveillance videos	Two mice	Effectively detect the mice mating behavior with high precision rate	This approach does not perform high speed applications	Precision rate = 96.1%
[13]	On-line video object segmentation using illumination-invariant color-texture feature extraction and marker prediction	SegTrack v2 dataset and specific dataset	Robustly segment objects under dramatic changes in both appearance and illumination	The run time of this algorithm is not yet satisfactory	Sequence = frog Execution time = 583 (4.33 s) Sequence = monkey Execution time = 174 (2.48 s)
[14]	Moving objects segmentation and extraction based on motion blur features	Natural images, downloaded from the internet or captured with camera and cell phone	Contourlet transform is good	Low performance for segmentation process	Image = o True positive rate = 0.9557 False negative rate = 0.0071
[15]	Validation and theoretical justification of an LC-MS method for the animal species specific detection of gelatin	Bovine and Porcine	Acceptable and accountable technique performance is obtained	-	Porcine in bovine gelatin results: Mean recovery 89.0%, 84.5% and 94.1% at the 0.05%, 0.1% and 2.0% QC levels Bovine in porcine gelatin results: Mean recovery was 111%, 122% and 104% at the 0.05%, 0.1% and 2.0% QC levels
[16]	Agreement between passive infrared detector measurements and human observations of animal activity	Human activity and animal activity dataset	Good estimation of the relative activity of the group	Less intense for feeding activities	Spearman's correlation coefficient = 0.90 concordance correlation coefficient = 0.86
[17]	Robust abandoned object detection integrating wide area visual surveillance and social context	PETS2006 and SUBITO datasets	Improve the tracking accuracy	Low precision and recall value	Ruleset = owner + group Recall = 0.38 Precision = 0.47
[18]	Vanishing point detection for visual surveillance systems in railway platform environments	18 rail platform environments	Very good results for detecting vanishing points in Manhattan-like scenes	-	Vanishing points unsuccessfully detected 1) Outdoor scenes Mean error (low resolution) = 126.28 Mean error (high resolution) = 7.81

					2) Indoor scenes Mean error (low resolution) = 59.97 Mean error (high resolution) = 2.34
[19]	Detecting animals in African Savanna with UAVs and the crowds	Kuzikus dataset	High recall rate	Low precision value	1) Detection Scores = 100 True positive rate = 0.85 False positive rate = 0.3 2) Detection Scores = 300 True positive rate = 0.84 False positive rate = 0.3
[20]	Wild Animal Detection using Discriminative Feature-oriented Dictionary Learning and clustering techniques	Caltech 101 dataset	Low complexity and high true positive rate	-	Accuracy = 93% True positive rate = 97%

IV CONCLUSION

In this paper, the different images and videos based object detection techniques are studied and compared in different environments to analyze the performance. From this table, Deep Convolutional Neural Networks has low accuracy. Automatic Wild Animal Detection has Low F-measure value, Detecting Kangaroos in the Wild: The First Step towards Automated Animal Surveillance has low precision and so on. Hence, Wild Animal Detection using Discriminative Feature-oriented Dictionary Learning and clustering has high true positive rate. The comparison table shows how images and videos based object detection techniques performed in different environments with different datasets. Thus due to the high accuracy the proposed work is on wild animal detection using Discriminative Feature-oriented Dictionary Learning and clustering.

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