International Journal of Application or Innovation in Engineering & Management (IJAIEM)
Web Site: www.ijaiem.org Email: editor@ijaiem.org
Volume 6, Issue 8, August 2017 **ISSN 2319 - 4847**

Wildlife Conservation by detection and Tracking of animals through image processing

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ABSTRACT

Threatened by habitat loss, poaching, pollution and other factors, wildlife species across the globe are declining in number at an alarming rate. Wildlife Conservation Society have been monitoring endangered wildlife populations for more than 100 years. For decades, traditional capture and tag methods have been a primary tool, but they are not the most efficient when dealing with large animals and animals in remote locations. The computer vision technology may revolutionize the way endangered wildlife in remote areas of the world are counted and monitored. The ability to identify individual animals is a prerequisite for many questions in behavioral ecology, cognitive research, conservation monitoring, and wildlife epidemiology. With the increasing availability of remote audiovisual recording devices, such as camera or video traps, standardized data collection has become much easier, in particular in the wild. Yet there are few techniques available to rapidly process the biologically relevant information contained in the data gathered.

Keywords: ***Visual prior, animal tracking, animal recognition, sparse coding, transfer learning.***

1.INTRODUCTION

Concentrating on creature conduct used to imply going under the wild Also making point by point notes around animals. Now, biologist-coders need aid figuring out how to utilize machine dream systems will change over the horde motions of animals substantial and little under crunch capable information.

Wildlife-based ecotourism may be quickly expanding in popularity, particularly The point when emphasizing huge mammals to their characteristic earth untamed life review might have been When recognized a non-consumptive human action with minimal alternately no sway with respect to animals. However, later Look into need nullified this suspicion Also instep uncovered how untamed life review exercises need negatively influenced animals. On exactly instances, ecotourism need benefited animals. However, these certain impacts would site specific, not totally ranging, What's more not imparted by know distinctive animals at these destinations. Thus, observing of mankind's affects ahead untamed life populaces that need aid the centering for ecotourism exercises is fundamental to guarantee that those wellbeing for single person animals What's more populaces will be not sacrificed to the economic, social, What's more instructive additions about ecotourism.

Untamed life administrators utilize an assortment about strategies that fluctuate in their effectiveness Also adequacy with screen untamed life around ecotourism locales. The universal strategies to population-scale information collection, for example, mark-recapture alternately flying counts, would work escalated consideration What's more greatly expensive. As an elective or supplement on these methods, the utilization about Polaroid systems, which gather data generally in the nonattendance of human operators, will be expanding clinched alongside Notoriety. Cameras bring those extra focal point that their method for information gathering will be lesquerella meddling or disruptive of the animals being monitored. To example, if animals' behavioral reactions with ecotourists need aid for interest, a as a relatable point information gathering system will be to utilize a on location eyewitness with perform those essential close-range perceptions. These spectators face two issues. In it might be incomprehensible with gather information the information that speaks to creature conduct technique for "ecotourist absence" though the observer's vicinity generates An comparable behavioral reaction Similarly as an ecotourist. Second, topolatry Also vegetation during a webpage might extremely breaking point those observer's capacity with perceive those central animals. Two systems to purpose those topolatry issue need aid the vocation from claiming extra spectators stationed toward key areas on gap the absolute observer's occasion when between Different ranges. Utilization of extra spectators builds human action in the territory which might perplex At whatever human effect following continuously embraced. The last alternative declines eyewitness duration of the time went through to each area, which lessens test sizes making indicator location Furthermore dissection that's only the tip of the iceberg testing. Therefore, it is invaluable to utilize Polaroid frameworks will remotely gather information data, without obstruction from human spectators. However, cameras produce a lot of data, which need aid normally sort program manually with gather information those required information. Likewise PC dream researchers, there may be an incredible chance will help common researchers

Eventually Tom's perusing computerizing parts of the feature dissection transform. Untamed life observing may be vital for keeping track about creature development patterns, habitat utilization, populace demographics, snaring What's more poaching episodes and breakouts. The important majority of the data that need various management applications, including the arranging for great prologue and evacuation methodologies of jeopardized untamed life species. Those principle commitment from claiming this fill in is Creating an arrangement should help biologists over information gathering. Association of the paper is as follows, area ii depicts those related work, segment iii portrays those recommended fill in and area iv provides for the effects.

2.RELATED WORK

There will be a rich written works done object following and An careful survey ahead this theme camwood make found done [28]. To manage the from claiming expansive item Furthermore foundation manifestation variations, The majority late following calculations concentrate on Creating hearty article representational schemes.

Since it will be challenging to Figure An situated for offers that need aid invariant will presence varieties of focus Questions Also backgrounds, Taking in calculations need been received for this errand. In light of a particular former of the target, an article model could a chance to be took in web. Bootleg et al. [4] gain An subspace model on speak to target Questions at altered sees. To [5], dark et al. Augment their subspace representational technique to An mixture model which could finer represent item manifestation. Avidan [1] employments a set for vehicle Furthermore non-vehicle pictures gathered internet with take a classifier for auto following. Constantly on these strategies rely vigorously on the particular former. That is, these systems would produced to particular Questions about enthusiasm. When every one could be allowed sees of the target are referred to in front of tracking, object manifestation models camwood be well constructed. Notwithstanding for the vast majority real-world following applications, it may be challenging on identify at conceivable presence varieties from claiming Questions. Therefore, such following calculations need restricted requisition domains.

Various versatile manifestation models have been as of late recommended to item following. Previously, these algorithms, article representational camwood make initialized Also updated for internet perceptions without whatever former. Jepson et al. [13] take a gaussian mixture model by means of an on the web desire expansion (EM) calculation on represent target presence varieties Throughout following. Aside from mixture models, incremental subspace systems In light of PCA alternately its variants have been utilized to on the web article representational [24], [17]. Will beat those issue of incomplete occlusion, meager representational need likewise been used to object following [21]. To [15], the writers extends those accepted molecule sifting skeleton with various progressive and perception models should represent target presence variety brought on Eventually Tom's perusing progress from claiming pose, illumination, scale and in addition fractional impediment.

Article following need also been posited Concerning illustration An double order issue. Collins et al. [7] recommend a strategy on select discriminative color Characteristics on the web for following while Avidan [2] employments web boosting technique with arrange pixels having a place will forefront What's more foundation. Recently, various methodologies have been suggested on manage the float issue At overhauling those took in presence model or classifier on the web for recently got following outcomes. Grabner et al. [11] view every last one of article majority of the data comparing of the following comes about Concerning illustration unlabeled information Furthermore adjust a classifier inside the semi-supervised Taking in skeleton. Babenko et al. [3] utilize various example Taking in (MIL) with handle vaguely marked certain Also negative information acquired web to decrease visual float. Kalal et al. [14] recommend An system with handle lopsided tests which exploits those underlying structure will select sure Furthermore negative tests to on the web redesign. All these following calculations don't expect At whatever former in regards to the target item population What's more might a chance to be connected on various issues. However, constant object following for these techniques is troublesome Similarly as it may be not clear if the updated visual data may be right or not (e. G. , new perceptions might hold numerous picture areas starting with those foundation and hence inaccurate majority of the data may be updated).

Meager coding calculations model a watched case Similarly as a straight consolidation of a few components starting with a through finish lexicon. The later improvement about meager coding representational need pulled in much enthusiasm and need been utilized within picture de-noising [8], [20], picture arrangement [23], [27] Also article following [21]. These routines bring turned out that Taking in lexicon from information outperforms pre decided (fixed) ones (e. G. , wavelet) since the previous camwood essentially decrease reproduction slip [8]. Di_erent from the representations In light of PCA Furthermore its variants [24], [17], such meager models don't force that those bases in the word reference make orthogonal, which permits All the more adaptability with adjust those representational of the information [19]. Done [21], those meager representational of a focus object will be attained Eventually Tom's perusing upgrading an target work which incorporates two terms: you quit offering on that one measures the reproduction slip and the different measures those sparsity. However, these strategies need aid generative In its center (based ahead reproduction error) to figuring out following comes about What's more need aid not provided to recognize focus. What's more foundation patches. Previously, [23], the writers do meager coding looking into crude picture patches for picture arrangement. For [27], those writers perform meager coding for filter features [18] Also accomplishes state-of-the-symbolization execution for picture order with respect to general population benchmarks.

3.LEARNING VISUAL PRIOR WITH SPARSE CODING

We first present how visual prior is learned from numerous images of various animal classes. Although we can get a large number of real-world images, there is no straight forward method to use and correspond to generic visual prior in the tracking literature. In this paper, sparse coding is used to learn the visual prior from large image sets of animal with an over complete dictionary

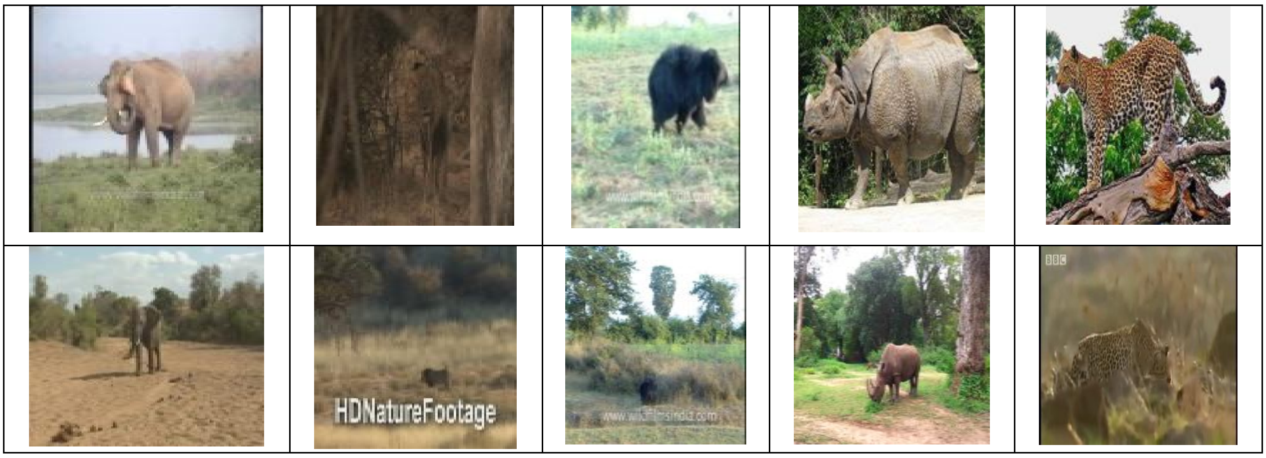

Fig.1 Sample Images for learning Visual Prior

- **Learning Dictionary**

SIFT choosenas the basic appearance descriptor in our tracking method. We extract the SIFT descriptors from overlapped patches of each gray scale image and learn the dictionary in an unsupervised manner. Let $X=[x_1 \ldots x_n] \in R^{m*n}$ be the SIFT descriptors we extract from the image set, where m and n are the dimensionality of each SIFT descriptor and the number of SIFT descriptors, respectively. The dictionary is denoted as $D[x_1 \ldots x_n] \in R^{m*k} (k \gg n)$ .The images in the dictionary is classified as

$$\min_{D,\{a_i\}} \frac{1}{2}\sum_{i=1}^{n}\|x_i - D\alpha_i\|^2 + \beta \sum_{i}^{n}\|\alpha_i\|_1 \quad (1)$$
$$\text{subjected to } \|d_j\|_2^2 \leq 1 \; \forall j \in \{1, \ldots, k\}$$

Where $a_i = R^k$ is the sparse coefficient vector of $x_i$parameter β is a tradeoff between reconstruction error and sparsity. To enlarge the sparsity, we can increase β and vice versa. Although there is a large number of SIFT descriptors extracted from the data set, is learned offline with the sparse coding method proposed.

4.ANIMAL REPRESENTATION FROM LEARNED PRIOR

The learned visual prior is represented by the over complete dictionary D. For animal tracking we transfer this prior by representing animal with D. For each SIFT descriptor a sparse coefficient vector is learned by performing l_1/l_2 sparse coding on the dictionary. Then, an animal is represented by applying multi-scale max pooling.

- **l_1/l_2 Sparse coding**

To represent an animal, we first extract the SIFT descriptors from their image patches and then encode them with the learned dictionary. Let $X=[x_1 \ldots x_n] \in R^{m*n}$ denote the SIFT descriptors extracted from an animal image, the l_1/l_2 sparse coefficient vector is calculated by

$$\min_{\alpha_i} \frac{1}{2}\|x_i - D\alpha_i\|_2^2 + \lambda_1\|\alpha_i\|_1 + \frac{\lambda_2}{2}\|\alpha_i\|_2^2 \qquad (2)$$

Where $\lambda_1$and $\lambda_2$are regularization parameters. When $\lambda_2 = 0$, it leads to the l_1 -norm sparse coding problem which has been widely used. The choice of the $\lambda_2 > 0$ makes the problem of Eq. 2 becomes strictly convex. The coding results

of all the descriptors in X are denoted by a sparse coefficient matrix $A=[x1\ldots xn] \in Rk*n$, where each column of A denotes the coding result of the SIFT descriptor for an image patch.
With $l1/l2$ sparse coding, the SIFT descriptors from different animal can be encoded by different bases in the dictionary. Thus, sparse coding can achieve a much lower reconstruction error.

- ***Multi-scale max pooling***

For the tracking task, we need to define animal level feature for a target or background sample over the sparse representation matrix A. There exist numerous methods for representing an animal with a set of descriptors, and here we use a pooling function which operates on each row of A and obtain a vector $b \in Rk$ Since each row of A corresponds to the response of all local SIFT descriptors in X to one specific basis in dictionary D, different pooling functions may generate different image statistics. To make the representation more robust to local spatial translations, we use the max pooling function on the absolute sparse codes

$$bi=\max\{|ai,1|\ldots..|ai,N|\} \quad (3)$$

wherebi is the i^{th} element of b and $ai,j$is the element of i^{th}row and j^{th} column of A.

To preserve the spatial information and local invariance, we use multi-scale max pooling to obtain the object level representation. This pooling process searches across different locations and over different scales of the animal image and combines all local maximum responses. In this work, it is implemented by dividing the whole animal image into M non-overlapped spatial cells, applying max pooling on the coding results of descriptors in each cell and concatenating the pooled features from all the spatial cells

$$z=[b1T\ldots..bMT]T, \quad (4)$$

Where $bi$the max pooling result of the ith spatial cell, M is is the number of spatial cells, and $Z=\in$ RMK With this process, we obtain a pyramid representation of an animal which is robust to local transformation.

5.ANIMAL TRACKING VIA SPARSE PROTOTYPES

After extraction of SIFT features, sparse coding, and multi-scale max pooling, we obtain a spatial pyramid representation for each animal image.

- **Proposed Tracking Algorithm**

Animal tracking can be considered as a Bayesian inference task in a Markov model with hidden state variables [5]. The sparse representation of the animal is shown in figure2.Given a set of observed images$Yt=\{Y1,Y2,\ldots Yt\}$ at t^{th} frame, We estimate the hidden state variable Xt recursively as

$$p(Yt)\alpha\, p(Xt)\int p(Xt-1)p(Yt-1)dxt-1 \quad (5)$$

Where $p(Xt-1)$represents the dynamic (motion) model between consecutive states, and $p(Yt)$ denotes observation model that estimates the likelihood of observing Yt at state Xt. The optimal state of the tracked animal given all the observations up to t^{th} frame is obtained by the maximum a posteriori estimation over N samples at time t by

$$\hat{x}_t = \arg_{\chi_t^i} \max\, p\left(y_t^i \mid x_t^i\right) p\left(x_t^i \mid x_{t-1}\right), i = 1, 2, \ldots\ldots\ldots. N \quad (6)$$

Where Xti indicates the i^{th} sample of the state Xt and Yti denotes the image patch predicated by Xti

- **Dynamic Model**

In this paper, an affine image warp to model the target motion between two consecutive frames is applied. The six parameters of the affine transform are used to model $p(Xt-1)$of a tracked animal. Let $XT=\{xt,yt,\theta t,st.\alpha t,\phi t\}$where $xt,yt,\theta t,st.\alpha t,\phi t$ denote x, y translations, rotation angle, scale, aspect ratio, and skew respectively. The state transition is formulated by random walk, i.e., $p(Xt-1)=N(Xt;Xt-1,\psi)$ where ψ is diagonal covariance matrix.

- **Observation Model**

If no occlusion occurs, an image observation ytcan be assumed to be generated from a subspace of the target animal spanned by **U** and centered at **μ**. However, it is necessary to account for partial occlusion in an appearance model for robust animal tracking. We assume that a centered image observation $Yt(Yt=Yt-\mu)$ of the tracked animal can be represented by a linear combination of the PCA basis vectors U and few elements of the identity matrix **I** (i.e., trivial templates), i.e.$Yt=UZt+et$ we note that U consist of a few basis vectors and $Zt$is usually dense. On the other hand,et accounts for noise or occlusion. If there is no occlusion, the most likely image patch can be effectively represented by the PCA basis vectors and coefficients corresponding to trivial templates (referred as trivial coefficients) tend to be zeros. On the other hand, a candidate patch that does not correspond to the true target location (e.g., miss-aligned sample) often leads to a dense representation. If partial occlusion occurs, the most likely image patch can be represented as a linear combination of PCA basis vectors and very few numbers of trivial templates Based on these observations, we note that the precise localization of the tracked animal can be benefited by penalizing the sparsity of trivial coefficients. For each observation corresponding to a predicted state, we solve the following equation efficiently using the proposed algorithm

$$L\left(z^i, e^i\right) = \min_{z^i, e^i} \frac{1}{2}\left\|\bar{y}^i - Uz^i - e^i\right\| + \lambda\left\|e^i\right\|, \quad (7)$$

And obtained zi and ei, where I denotes the i-th sample of the state x

The observation likelihood can be measured by the reconstruction error of each observed image patch

$$p\left(\bar{y}^i \middle| x^i\right) = \exp\left(-\left\|\bar{y}^i - Uz^i\right\|_2^2\right). \quad (8)$$

However, Eq. 8 does not consider occlusion. Thus, we use a mask to factor out non-occluding and occluding parts

$$p\left(\bar{y}^i \middle| x^i\right) = \exp\left[-\left(\left\|w^i \,\Theta\left(\bar{y}^i - Uz^i\right)\right\|_2^2 + \beta\sum\left(1 - w^i\right)\right)\right]. \quad (9)$$

Where wi=[w1i,w2i,…..,wdi] is a vector that indicates the zero element of ei ,⊙ is the Hanamard product (elements wise product),and β is a penalty term (simply set to λ in this study). If the j-th term of ei (obtained from Eq. 7), is zero then wji=1 otherwise wji=0 The first part of the exponent accounts for the reconstruction error of unconcluded proportion of the target animal, and the second term aims to penalize labeling any pixel as being occluded. The experimental results demonstrate the effectiveness of our formulation.

- **Update of Observation Model**

It is essential to update the observation model for handling appearance change of a target animal for visual tracking. The model degrades if some imprecise samples are used for update, thereby causing tracking drift. Instead, we explore the trivial coefficients for occlusion detection since the corresponding templates are used to account for noise. First, each trivial coefficient vector corresponds to a 2D map as a result of reverse raster scan of an image patch. A non-zero element of this map indicates that pixel is occluded (referred as occlusion map). Second, we compute the ratio η, of the number of nonzero pixels and the number of occlusion map pixels. We use two threshold tr1 and tr2 to describe the degree of occlusion (e.g., tr1 = 0.1 and tr2 = 0.6 in this project). Third, based on the occlusion ratio η, we apply one of the three kinds of operations: full, partial, and no update. If η < tr1, we directly update the model with this sample. If tr1 ≤ η ≤ tr2, it indicates that the animal is partially occluded. We then replace the occluded pixels by its corresponding parts of the average observation **μ**, and use this recovered sample for update. Otherwise if η > tr2, it means that a significant part of the target animal is occluded, and we discard this sample without update. Several cases regarding three update scenarios. After we cumulate enough samples, we use an incremental principal component analysis method [5] to update our observation model (i.e., PCA basis vectors **U** and the average vector **μ**).

6.Tracking Architecture Design

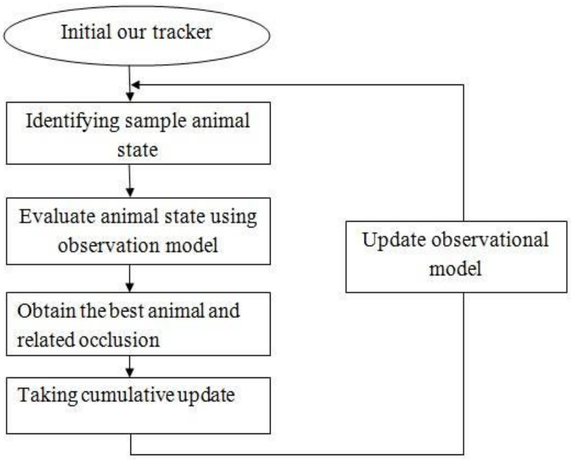

Fig.2: Tracking algorithm. It consist of three main parts: dynamic model, observation model, & update model

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Web Site: www.ijaiem.org Email: editor@ijaiem.org
Volume 6, Issue 8, August 2017 ISSN 2319 - 4847

6.RESULTS

The proposed algorithm is implemented in MATLAB which runs at 2 frames per second on a pc with Intel i5-2450M CPU with 4GB memory. For each sequence, the location of the target animal is manually labeled in the first frame. For PCA representation, each image observation is normalized to 32×32 pixels and 16 eigenvectors are used in all experiments. In addition, we use 1024 trivial templates. As a trade-off between computational efficiency and effectiveness, 600 particles are used and our tracker is incrementally updated every 5 frames. The regularization constant λ is set to 0.05 in all experiments.

black-bear#0 black-bear#86 black-bear#113

Rhinoceros#0 Rhinoceros#78 Rhinoceros#125

Blackbuck#16 blackbuck#114 blackbuck# 150

Nilgai#33 nilgai#120 nilgai#150

Elephant#42 **elephant#69** **elephant#160**

Fig.3 : experimental results

7.CONCLUSION

This paper presents a robust tracking algorithm via the proposed sparse prototype representation. In this paper, we explicitly take partial occlusion and motion blur into account for appearance update and animal tracking by exploiting the strength of subspace model and sparse representation. Experiments on challenging image sequences demonstrate that our tracking algorithm performs favorably against several state-of-the- art algorithms. As the proposed algorithm involves solving l minimization problem for each drawn sample with the proposed model, we plan to explore more efficient algorithms for real-time applications. We will extend our representation scheme for other vision problems including object recognition, and develop other online orthogonal subspace methods (e.g., online NMF) with the proposed model. In addition, we plan to integrate multiple visual cues to better describe objects in different scenarios and to utilize prior knowledge with online learning for more effective object tracking.

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