WILD ANIMALS POPULATION ESTIMATION FROM THERMOGRAPHIC VIDEOS USING TENSOR DECOMPOSITION

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Abstract

In this paper an algorithm is presented for wild animals population estimation through background modelling and subtraction in videos captured by thermographic cameras. In order to obtain low-rank and sparse representation of the video content on a frame-by-frame basis several decomposition techniques are tested, namely the Robust Principal Component Analysis (RPCA) with its Go implementation (GoDec), Low-rank matrix completion by Riemannian optimization (LRGeomCG), Robust Orthonormal Subspace Learning (ROSL), and Non-negative Matrix Factorization via Nesterov's Optimal Gradient Method (NeNMF). Promising results are obtained in terms of accuracy and the approach seems applicable in agronomy, protection of the natural environment, forestry and others.

1. INTRODUCTION

Thermography has been long employed into numerous applications related to remote sensing, mechanical design at the stage of component durability testing, medical treatment, civil and military surveillance and others.

In [1] Yang and He investigate wide range of thermographic methods based on optical and non-optical excitation to locate damages in composites as a non-destructive approach. They group the various implementations based on the nature of the heat inductor as optical, laser, eddy current, microwave, vibro- and ultrasound. Classification of known realizations has also been provided according to the type of the heating function, style, position and motion. At the stage of registered signals processing some of the designers rely on tensor decomposition. Gao et al.[2] turn towards the estimation of fatigue and residual stress by incorporating spatial-transient-stage tensor along with Tucker decomposition taking into account the variation of material qualities over time. Positive results are reported from analyzing gear fatigue. Further the authors [3] confirm the significant level of correlation between the deviation of the physical properties of tested steel materials and the mathematical models based on tensor analysis when eddy currents are applied in a pulsed manner.

Active thermography is another mean for composites exploration by analyzing captured images for detecting various defects [4]. Series of infrared pictures are ordered in time of recording and then adjacent pixels from consecutive planes are processed. The first derivative over the selected spatial direction together with two-dimensional wavelet transform yielded most accurate results into detecting cracks.

Series of thermo-images are also under consideration by Garbe et al. [5] who propose to have from them a complex motion estimation. Heat dissipation on a time scale as a diverging process undergoes analysis with the local gradient technique. Atmospheric interaction with the ocean surface is the primary focus with a possible application to non-destructive testing and botany as well. This method permit accuracies as high as one tenth of a pixel.

Thermography allows not only pattern analysis but also separation from thermos-series [6]. Non-negative pattern discriminative scheme when eddy current acts as a driver in pulsed thermography for detecting particular patterns and their temporal change is applicable in this unsupervised approach. It is known with its scale invariance.

Aerospace composites are another object of testing under the use of eddy current [7]. In this approach signal reconstruction along with a pattern recognition techniques take place. Relatively large surface areas under processing and short time intervals are distinct properties of this method. Tucker decomposition helps into near-surface defects spotting from a few hundred frames captured forming the three-dimensional tensor.

Tensor regression based on engaged penalties are in the basis of an image-based prognostics approach [8]. Series of degradation images supports the prediction of the residual product lifetime. Tensors give the opportunity for dimension reduction by projection to a sub-space with information sparing capability. Further, regression acts a mapping tool for the time-to-failure data and CANDECOMP/ PARAFAC (CP) along with Tucker decomposition serve as parameter estimator for the higher dimension configuration. Testing with a data from rotating machinery provides positive practical results.

Another highly productive and current approach for nondestructive testing is the microwave termography [9]. Zhang et al. present a review on various techniques employing it pointing out its advantages – selection of the area of heating, energy efficiency, power uniformity, volume affecting and ability for particular penetration. Despite being extremely useful in quality control and industrial continuous monitoring its applicability in surveillance applications is not mentioned.

Gear inspection in wind turbines at limited time intervals during general maintenance for fatigue discovery prove useful according to Gao et al. [10]. The implementation of the tensor apparatus over thermal data obtained by inductive principle it becomes possible to supply early warning on wearing out such components.

Despite the vast amount of practical implementations of thermographic sequences, most often applying tensor decomposition schemes, in non-destructive testing, quality control, fault diagnosis or investigating complex interaction processes of physical nature it seems that thermography based surveillance systems is another major field that deserves attention into employing these methods. In this study we are investigating the applicability of 4 multidimensional decomposition algorithms for wild animals population estimation through background modelling and subtraction. The tested algorithms are presented in Section 2, followed by experimental results in Section 3. The latter are discussed in Section 4 with useful guidelines about the future use of this algorithms and then the paper ends with a conclusion.

2. ALGORITHMS DESCRIPTION

2.1. GODEC

When establishing certain relations among parameters describing processes it is practical to use compressed representations and most of the processing is done by matrix completions. The latter are done by low-rank formations $\mathcal{L}$ and sparse entities $\mathcal{S}$. The Go decomposition [11] is efficient tool in estimating these parts given the input matrix as:

$$\mathcal{X} = \mathcal{L} + \mathcal{S} + \mathcal{G}, \tag{1}$$

where $\mathcal{G}$ is the present noise within the data. Alternative association is made according to:

$$\left| \begin{array}{l} \mathcal{L} \cong \mathcal{X} - \mathcal{S} \\ \mathcal{S} \cong \mathcal{X} - \mathcal{L} \end{array} \right. . \tag{2}$$

Speeding up the whole process comes from bilateral random projections [11]. It is also applicable to matrix completion. Given the objective function:

$$f = \|\mathcal{X} - \mathcal{L} - \mathcal{S}\|_F^2 \tag{3}$$

Zhou and Tao [11] prove that it goes to a local minimum while $\mathcal{L}$ and $\mathcal{S}$ strive to their optimums. The procedure is robust as the authors report compared to Robust PCA and OptSpace.

2.2. LRGEOMCG

LRGeomCG [12] represent low-rank matrix completion where the optimizing procedure is implemented directly given a multitude of matrices with a fixed rank. This task may be expressed as:

$$\left| \begin{array}{c} \text{minimize}_{\mathcal{X}}\, f(\mathcal{X}) := \frac{1}{2}\|P_\Omega(\mathcal{X} - \mathcal{A})\|_F^2, \\ subject\ to\ \mathcal{X} \in \mathcal{M}_k := \\ \{\mathcal{X} \in \mathbb{R}^{mxn} : rank(\mathcal{X}) = k\}. \end{array} \right. \tag{4}$$

In (4), applying the Frobenius norm *F*, $\mathcal{A}$ is *mxn* matrix on subset Ω, part of entire set of inputs {1÷*m*}x{1÷*n*}. The holistic minimizer has a rank of *k*. $\mathcal{M}_k$ is a smooth manifold over $\mathbb{C}^\infty$ and the optimization function is denoted as *f*. The author reports good scalability in solving large-scale tasks with higher efficiency than some of the other well known algorithms of the same type.

2.3. ROSL

Computational sparing low-rank recovery is possible by applying ROSL [13] in the case of lacking samples from the input data. The approach is quite practical within the computer vision field. A new measure considering the rank of the sparse representation over orthonormal subspace and a coding algorithm for rank minimization makes it possible to have quadratic complexity of the matrix size for the procedure. Shu et al. [13] prove that the new rank measure is limited from below by the nuclear norm. Random sampling leads to linear complexity in further optimizing the algorithms according to the authors and outperforms some of the earlier decompositions.

2.4. NENMF

Non-negative matrices could undergo decomposition using a product of a couple of factors in two-dimensional form with the condition to be also non-negative. NeNMF [14] uses Nestorov's optimal gradient approach over one factor optimizing it alternatively with another of fixed form. Matrix factor is recalculated at each step by the projected gradient method over a predetermined position for a search and a Lipschitz constant determines the amount of increment. Approximation accuracy and computational time efficiency are proved to be higher than that of multiplicative update rule and projected gradient method alone [14].

2.5. Motion-based multiple object tracking (MT)

As a mean for comparison with the above four described algorithms MT [15] has been tested to evaluate both the computational efficiency and the accuracy provided. Working entirely in spatial domain it is widely used in the practice consisting of the following stages: entity objects construction, tracks initialization, detecting objects, predicting track changes, assigning tracks to objects, continuous update of generated tracks and outputting the results.

3. EXPERIMENTAL RESULTS

The experiments are implemented on a PC with Intel Core i5 x64 CPU (4 cores) operating at 3.1 GHz, 12 GB operational memory. The OS is Linux Ubuntu 14.04 LTS and the testing environment – Matlab R2016a. All decomposition algorithms come from LRSLibrary v. 1.0.10 [16]. Testing database comprises of six thermographic videos (Tabl. 1) containing in various frames from one to tens of wild species.

The average decomposition (DT) and full processing time (FT) for all 6 videos, including input-output operations to the hard drive, are given in Table 2.

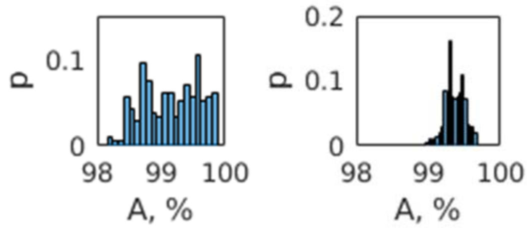
Table 1. Testing videos

Video	Width, px	Height, px	FPS	Frames
1	320	180	29.97	211
2	400	224	29.97	211
3	400	224	23.98	145
4	400	300	29.97	211
5	400	300	20.00	141
6	400	300	20.00	140

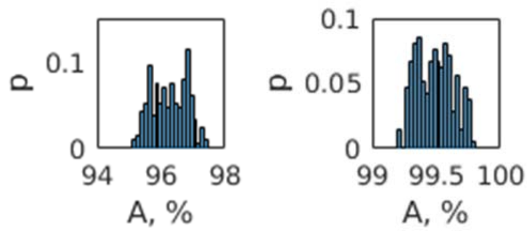
There also appears the average animal detection accuracy (A). In Fig. 1 its distribution (p) for every video reveal how stable each of the tested algorithms are.

Table 2. Average processing times and detection accuracy

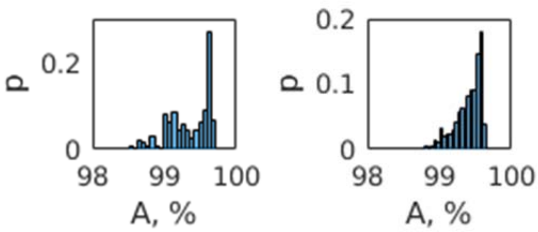
Algorithm	DT, sec	FT, sec	Accuracy, %
GoDec	1.96	5.54	98.53
LRGeomCG	4.74	8.43	99.20
ROSL	9.01	12.45	96.51
NeNMF	0.36	4.01	99.30
MT	4.22	-	63.55



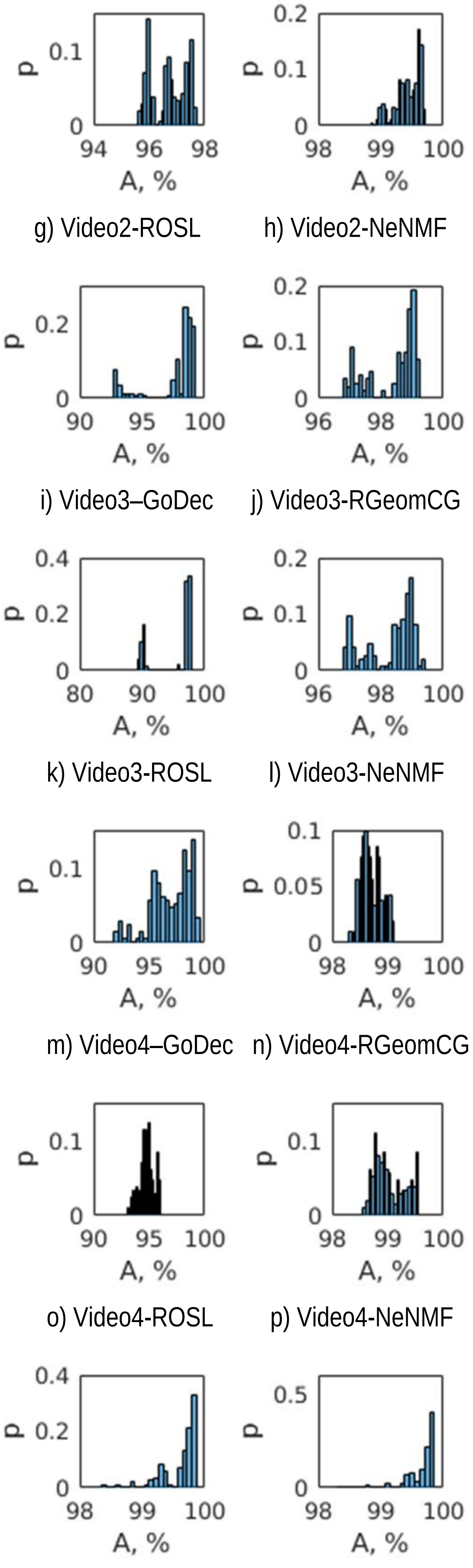
a) Video1–GoDec b) Video1-RGeomCG



c) Video1-ROSL d) Video1-NeNMF



e) Video2–GoDec f) Video2-RGeomCG



g) Video2-ROSL h) Video2-NeNMF

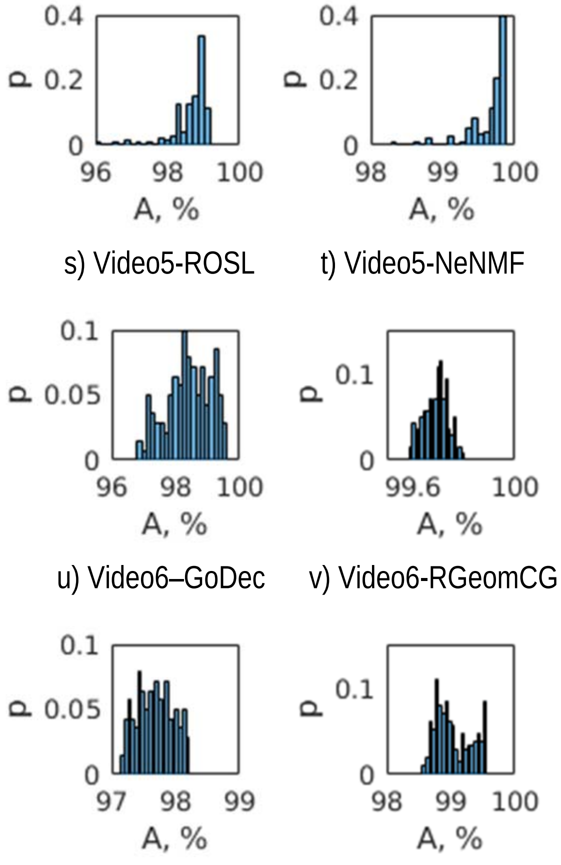
i) Video3–GoDec j) Video3-RGeomCG

k) Video3-ROSL l) Video3-NeNMF

m) Video4–GoDec n) Video4-RGeomCG

o) Video4-ROSL p) Video4-NeNMF

q) Video5–GoDec r) Video5-RGeomCG



s) Video5-ROSL t) Video5-NeNMF

u) Video6–GoDec v) Video6-RGeomCG

w)Video6-ROSL x) Video6-NeNMF

Fig. 1. Accuracy distribution across videos

4. DISCUSSION

The fastest algorithm is NeNMF and the slowest is ROSL, 25 times slower. The MT, a defacto industry standard in numerous practical surveillance applications, which we use to compare to the 4 tensor decomposition algorithms, falls somewhere in the middle as time performance with 4.22 sec (Table 2). Not so is the case with its accuracy – more than 30% lower than all the other methods which are very close with a difference of no greater than 3% and in the same time nearing 100%. NeNMF is the most accurate approach with 99.30% followed by only 0.10% by LRGeomCG. With a few exceptions, the distribution of accuracy is relatively symmetrical (Fig. 1).

The reason for the considerable lower performance of MT lays behind the actual content of the testing videos. While the accuracy for video 1 is 74,16% and may be considered as acceptable, the content of the video comprises of relatively large (in relative number of pixels) objects of interest (deers) – Fig. 2.a. In contrast, video 2 contains small objects for tracking (wild boars) closely located, significant portions of which are being missed or tracked as one object (Fig. 2b). Only 2 objects for tracking exist in video 3 (baby deers) and here MT achieves 100% accuracy but with 109% false positives due to slightly moving nearby objects with temperatures close to that of the animals (Fig. 2c). Accuracy falls considerably for the MT in video 4 with only 42,25% due to the extremely small objects to track (wild boars) and their large number (Fig. 2d). The perspective of capturing the video is panoramic taken high above the ground which leads to radial-like change of speed of the species even when they are moving at a constant rates. All these factors lead to that unsatisfactory result in this case. The accuracy is even smaller, just 16.31%, for video 5 which includes a family of wild boars – mother with babies which are significantly smaller in size and no detection occurs for them. Only the mature specimen has been spotted for around 1/3rd of the frames (Fig. 2e). A single deer captured at a close distance in video 6 (Fig. 2f) yields 100% accurate detections of its body by the MT. Lots of segmented detections at the boundaries of limbs and head lead to 96.43% false positives. It raises concerns for cases where multiple parts of a single connected body are moving at different speeds and sometimes in different directions. A problem that need to be resolved further by more advance analysis within the tracking algorithm.

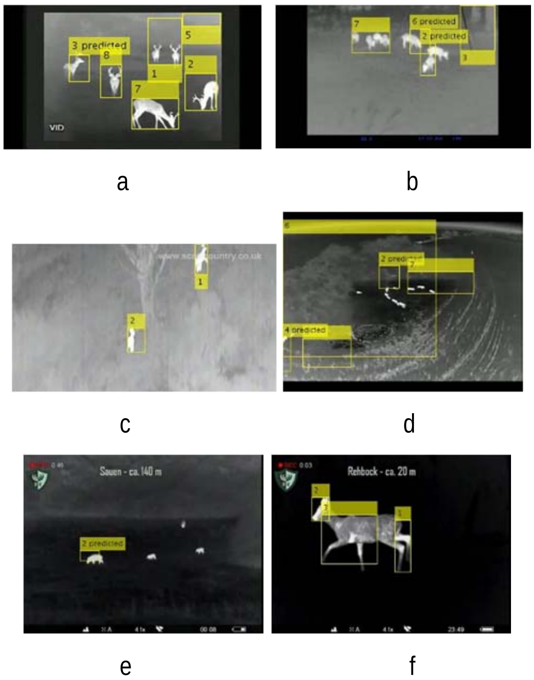


Fig. 2. Animal detections by MT

5. CONCLUSION

In this study the performance of GoDec, LRGeomCG, ROSL, NeNMF and MT algorithms is evaluated applied to the wild animals detection and tracking. High accuracy for the tensor decomposition based implementations of 98.39% on average is achieved. Execution times allow real-time processing when ported on the appropriate hardware and may be used in mobile environment. Further study is needed to enhance performance when dealing with smaller objects and in particular cases of camera perspectives, e.g. when filming from a drone.

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