Visual Animal Biometrics: Survey

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Abstract: Visual animal biometrics is an emerging research discipline in computer vision, pattern recognition and cognitive science. It is a promising research field that encourages new development of quantified algorithms and methodologies for representing, detection of visible features, phenotypic appearances of species, individuals and recognition of morphological and animal biometric characteristics. Furthermore, it also assists the study of animal trajectory and behaviours analysis of species. Currently, real-world applications of visual animal biometric systems are gaining more proliferation due to a variety of applications and use, enhancement of quantity and quality of the collection of extensive ecological data and processing. However, to advance visual animal biometrics will require integration of methodologies among the scientific disciplines involved. Such valuable efforts will be worthwhile due to the enormous perspective of this approach rests with the formal abstraction of phenomics, to build well-developed interfaces between different organisational levels of life. This study provides a comprehensive survey of visual animal biometric systems and recognition approaches for various species and individual animal based on their morphological image pattern and biometric characteristics. This comprehensive review paper encourages the multidisciplinary researchers, scientists, biologists and different research communities to design the better platforms for the development of efficient algorithms and learning models to solve the massive data processing, classification and identification of different species related problems.

1 Introduction

Visual animal biometrics is an emerging research field that develops quantified methodologies and formal techniques for representation and detection of visual features, phenotypic appearances of different species, individuals, morphological characteristics and behaviour analysis [1, 2]. Visual animal biometric is a pattern recognition-based system that fingerprints phenotypic appearances. It is similar to SLOOP animal identification system that retrieves salient information (features) from the morphological image pattern and biometric characteristics for the recognition of species and individual animal [1]. The primary objective of SLOOP system is to search and retrieve biometric features. The biometric features are extracted from the labelled images database of the species or individuals. The SLOOP system classifies the extracted features and recognises the species. Visual animal biometric system performs the recognition of species similar to recognition of minutiae points in human fingerprints. Moreover, visual animal biometrics can be applied to the better understanding and classifying phenotypic appearance of species, identify the location of the existence of our version with, a recognise the individual behaviour as well as to distinguish the morphological pattern of inter-class variation and intra-class species changes over the years [2].

A phenotypic appearance of species is defined as a composition of recognisable characteristics of any organisms, which includes morphological image pattern of species and biochemical or physiological properties [2]. The morphological characteristics include visual appearances, such as body structure, shape, colour, patterns (e.g. coat pattern, spot point pattern), size and specific structural features of organisms [2, 3].

Visual animal biometric-based recognition systems utilise both variability and uniqueness of coat patterns, vocalisations, movement dynamics and characteristics of body morphology. The conventional methodologies for species or individual recognition computationally interpret the required information about the appearances of different species in a scientific and systematic manner by using algorithmic formalisation approaches and developments. In general, they defined the various classes of species in highly objective measures based on their morphological and phenotypic appearances. Achieving the primary goals, high demand multidisciplinary collaborations among researchers, ecologists, biologist, engineers, computer scientists, statisticians and research groups or communities are needed to perform the depth level research in the visual animal biometrics. Visual animal biometrics develops widely on a longstanding, applied tradition in ecological and evolutionary studies of documenting and indexing of animal phenotypic appearances [2]. The classical works are useful for representing, indexing data and detecting animals dating back to the mid-1992s have used ordered sketch collections of different animals [4] and photographic image databases [5, 6].

Various species have a unique and discriminatory marking image patterns in their body, such as spot patterning (for the penguin, tiger, whale etc.) [7] stem from this era, prognosticating increase, shift and development closer to formal techniques for representing and detection of species or individuals. Documentation and photographic records based indexing techniques facilitate to objectify the phenotypic appearance of species for recognition purpose. However, these techniques consume more time for the pre-processing and searching the generated significant tags or metadata information automatically for the classification and representation of visual phenotype appearances, which is dependent on the skills of the producer and subject to observer error and bias [8].

Building on this foundation, currently better advancement in automatic recognition of individual, surveillance and biometric-based recognition systems have created a great plethora of complex approaches used to identify species and locate targets [9], analysis and assess of unique marking pattern of animals (e.g. coat patterns) during movement [10], pose variations [11], individuals [12], determine behaviour [13–15] and compute the discriminatory features for analysis of facial expressions [16]. In addition, system automatically caters the repeatable and formalised measures. These measures are generally independent of the subjective human based observation.

The computer vision and pattern recognition methodologies are highly applicable for representing, detecting the phenotypic appearances of animal and perform analysis at the depth levels for better monitoring and tracking of animal populations across ecology. Multidisciplinary researcher, biologists and ecologists have begun to test the approaches for representation and recognition of animals. They have customised the recognition algorithms fundamentally. Therefore, ecological and evolutionary researchers achieve and interpret the voluminous documentations, various photographic records and data of ecological field of different species across all populations. Current advances in algorithms in automated image-based tracking systems compromises the opportunities to remotely quantify and recognising the species or individual behaviour at different scales [16, 17].

The semi-automatic photo identification approaches have well established in fields, such as observation and tracking of marine species [18] and identification of wild species. It semi-automatic photo approaches enables the multidisciplinary researchers and marine scientists to track millions of species or individuals over time and space. A tedious work what can be achieved by manual recognition approaches [19]. Even more, innovative recognition and monitoring approaches have started to combine the animal biometrics with efficient sensor networks [20], crowdsourcing [21], cloud computing, machine learning algorithms [22, 23] to enhance the feasibility and impact of schemes to significantly improve the study of animal movement and behaviour of endangered species. For example, ACONE project [24] developed various classifications and recognition approaches for ivory-billed woodpeckers using high-resolution video and images for distinguishing an ivory-billed woodpecker from its neighbour (common Pileated Woodpecker). In the similar direction, online databases of the whale shark species, ECOCEAN Whale Shark Photo-Identification Library, it is a visual database for whale shark (Rhincodon typus) [25] used for their monitoring purposes. ECOCEAN whale shark identification library has been able to create the thousands of crowd-sourced sighting records [22] (http://www.whaleshark.org/). The shark identification library has applied for analyse the whale shark sighting data and learn more about these amazing creatures [26–28].

In the similar direction, University of Minnesota developed an animal biometric-based recognition system. The developed system is applied to study the behaviours of lions. The biometric-based system performs the behaviour analysis of lion in the groups and understanding how an entire community of large animals interacts. They have monitored 24 lions using monitoring and radio-tracking based animal biometrics-based systems in Serengeti National Park, Tanzania. Research group in University of Minnesota prepared the databases of wildlife animal. The size of the database is 300,000 images from 40 classes of mammals (subjects) [29].

Since last two decades, computer vision and pattern recognition approaches have gained more proliferation in the development of automated recognition systems and models for recognition of animals. The recognition systems recognise the animal based on their unique marking biometric characteristics, such as spot point or joint strips in coat pattern [1, 2, 22]. For example, zebra, whale shark [26], tigers and penguin recognised based on their phenotype appearances and unique marking biometric characteristics [30, 31].

The uniqueness and distinctiveness of animal appearance naturally is encoded by configurations of landmarks of the image pattern. The quantification process of the phenotypic appearance of animal has primary objective to measure the difference between biometric templates to discrimination and detect individual behaviour and morphological characteristics. It provides an independent to human observers which ultimately mitigate the common sources of variation and bias since human-based studies are affected by interpretation subjectivity and skill or experience.

The various recognition and matching approaches facilitate the comparability of studies across the different species populations in systematic manners. The autonomous sensors and audio-visual recording devices collect the data continuously in time, compared with limited, discrete time periods of human observers, manual process that increases the sample sizes. Furthermore, studies using well-established automatic identification benefited from the ability to handle different datasets at considerably higher speeds compared with human observers particularly relevant for tedious, repetitive tasks [10].

The performance degrades when conducting repetitive tasks because it needs the high accuracy for extended periods. Nowadays, high-speed performance-based electronic equipments, such as radio-frequency identification (RFID), automatic sensor and computers are in a better condition for this kind of data processing. Thus, researchers and scientists are motivated to emphasise to find out the solutions for the most complex aspects of various projects by automated animal pattern systems in animal biometric systems. The free availability of human resources becomes increasingly significant in budget limited and data-intensive studies for more complex tasks [32].

In Fig. 1, bounding boxes around the animal's body illustrates the detection of body parts, their morphological pattern in the video or still images as are given input source [33, 34]. For a given image as input, features are extracted from input images and extracted features are classified to perform the classification of the species. The face detection of [35], the configuration of unique marking of natural spot points for whale shark identification, the frequency spectrum of head motion of lion and locomotion recognition and histogram distribution of spot pattern configurations for penguin identification are shown in Fig. 1.

The remaining of this paper is organised as follows: Section 2 presents the concept of visual animal biometrics. Section 3 illustrates the major impacts of visual animal biometrics. Section 4 demonstrates the some visual animal biometrics systems for the recognition of species. Section 5 presents pre-requisite (requirements) for promising applications in visual animal biometrics. Section 6 provides details of traditional methodology for animal recognition. Section 7 illustrates details about applications along with technical challenges research communities, tools and data sharing. Section 9 illustrates the recognition and monitoring approaches of species or individual. Section 9 demonstrates the current state-of-the-art approaches in the visual animal biometrics. Finally, Section 10 is dedicated to concluding, discussions and future directions.

2 Visual animal biometrics and how recognised the phenotype appearance of animals

Visual animal biometrics is a pattern recognition-based system. It captures the biometric data from an individual, extracts a salient feature set from the data, compares the feature set against the feature set (s) stored in the database. After that, the system executes an action based on the result of the comparison [30, 31, 36] (shown in Fig. 2). The source for data acquisition is the measurable information which displayed because of the most discriminant feature of the anatomy (body structure), morphological characteristics and behaviour of the species. Typically, aspects of the animal appearances, its movement characteristics, and vocalisations are chosen and used as suitable biometric entities [2]. It is a difficult task to determine suitable biometric characteristics for the animal recognition, classification, and controlling, tracking and monitoring the animal population.

The selected animal biometric characteristics measured by acquisition devices known as sensors. It is sufficiently permanent, characteristic of the animal class of interest and universally demonstrated throughout the applicable for the study population. The unique marking patterns are coat patterns (e.g. joint stripes), spot patterning on African penguin [9] and tiger's body [12], cheetahs [13] and whale shark [14, 15]. These patterns have been shown to satisfy these criteria when these unique patterns used for visual identification of individual animals or different species. However, not all prominently visible and discriminatory set of features of biometric characteristics is more suitable for the recognition and classification of species in their habitats. Any injury or cut marks on white whale sharks [14–16, 37] and some scars on coat pattern are paramount for instances, yet its uniqueness and universality of these characteristics is short-lived since marks heal quickly. This temporal variability of various patterns of animals evidently limits their biometric systems use for long-term studies [18].

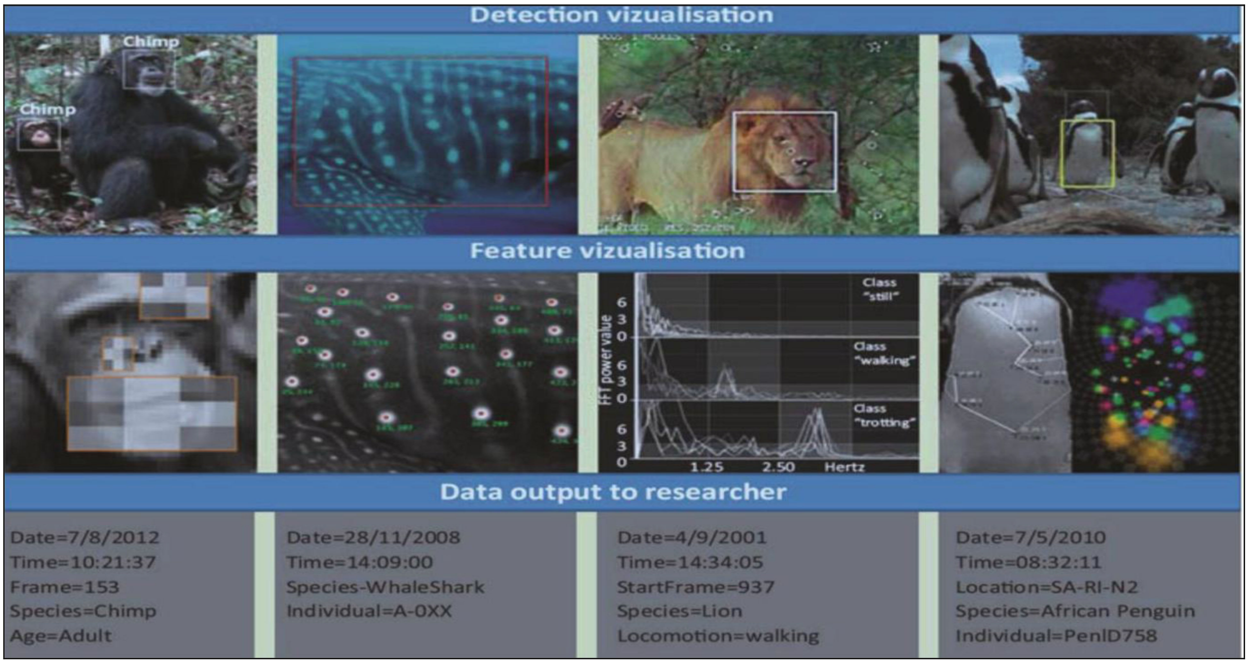


Fig. 1 *Visual animal biometric system detecting and classifying species and individual animal [2]*

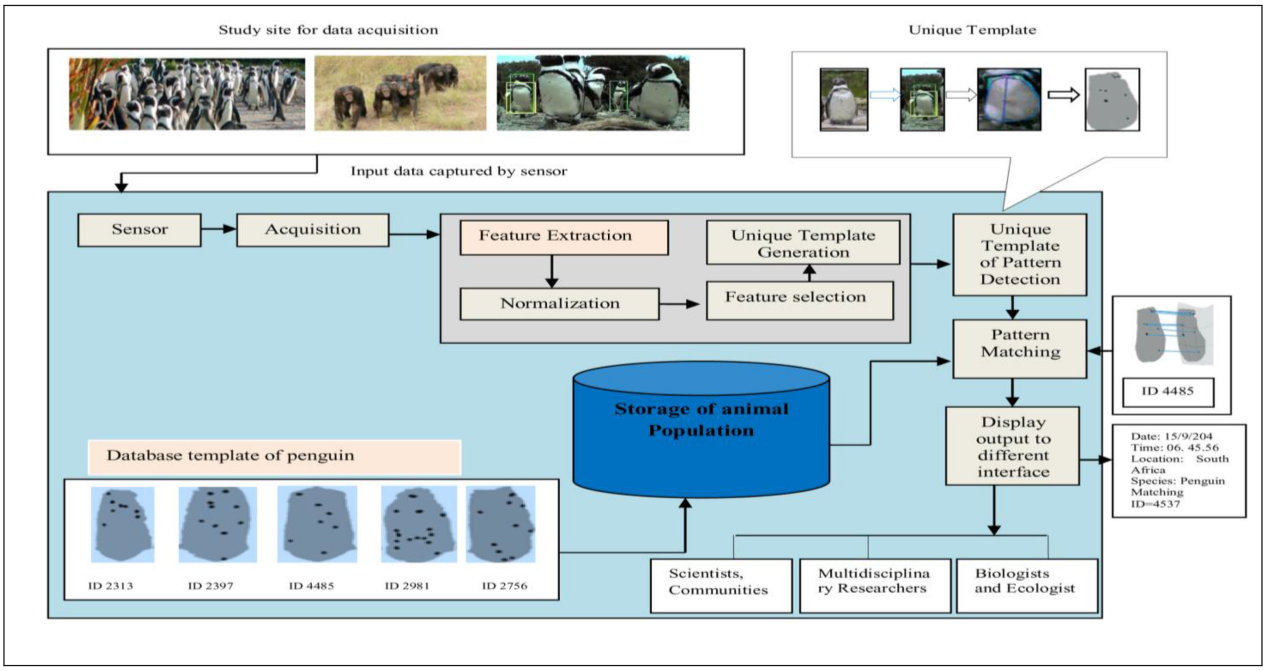


Fig. 2 *Illustration of major components of the visual animal biometric system. The flowchart illustrates how input data has been captured from a study site and performed the measurements and interpretations for the various multidisciplinary researchers. Each of the components is presented using individual African penguin recognition using different marking patterning such as spot pattern considered as an example*

Although, the correctness of such biometric entities of a species that requires revaluation in the most studies, proven that there is a need to design of automated visual animal biometric-based recognition systems contain all following components: (i) sensors for data acquisition, (ii) feature extraction and detection of species from captured data (pattern), (iii) storage capabilities for large database, (iv) similarity matching technique between train and query templates, (v) decision or action executed based on matching scores and threshold and (vi) utilisation of extracting features of characteristics by the interfacing of various applications or users. Visual animal biometric system is shown in Fig. 2.

In the acquisition step, various sensors, such as camera (e.g. surveillance camera) are applied to capture the data from the study sites for data acquisition. After acquisition phase, individual species are detected by face detection algorithms. The biometric features (e.g. the spot chest points of a penguin) are extracted from the captured data (e.g. video or image database). The extracted features are pre-processed and normalised for better representation in the feature space. The unique set of feature vectors are selected from extracted features and biometric templates are generated and stored in the animal template database. The storage of animal population is used as required database. In matching process, the small representation of scientific data (e.g. feature vectors) of each subject is matched and compared with other stored data of each subjects stored in the database. A test (query) image of species or individual animal is matched with the stored template database and computes the matching scores using similarity matching techniques for the recognition of individual animal. Finally, interface component reports the consistent output of the visual animal biometric system to different users, such as scientists, multidisciplinary researchers, biologists and ecologists and software system for further study and analysis [19].

The biggest challenges in visual animal biometrics included lens condensation within field cameras, destruction of camera traps by termites and chewed power that caters the cables and system shutdown due to the overheating (e.g. warm heating) and lack of power shortage. Hence, it is requirement to facilitate robust operation and mitigate the problems; visual animal biometric systems are often reduced to minimalist versions of what could be applied in controlled environments. This can be sufficient for many studies and several studies and monitoring purposes. For the controlled use, some measures like as flight velocity [20] or gait-type behaviour [24] are extracted from the low-quality video or image database. In any case, visual animal biometric systems perform the identification of species by matching of correspondences, the same species or same behaviours among multiple observations. Table 1 illustrates the literature review of visual animal biometric algorithms.

2.1 Visual animal biometrics for recognizing and profiling

Visual animal biometrics plays a significant role in the monitoring, tracking of animal, representation and detection of species. One of the most frequent applications of the biometric system is to identify individual animals and profile the behaviours of different species [30, 31, 47–49]. The uniqueness and distinctiveness of phenotype appearances usually is encoded by configurations of various landmarks on the body or unique marking pattern of species. For example, recognition of elephant's ear-nicks [38], spot patterns of penguin [50], tiger [51], stripe junctions in coat pattern of zebra [39], identification of Masai giraffe using the scale invariant feature transform (SIFT) features [52], recognition of cattle using muzzle point image pattern [48, 49] are similar to recognition of minutiae points in human fingerprint [53–56]. There is a trade-off between model variability versus constancy that typically favours either individual identification or species recognition due to unique features of pattern making of the individual animal. It is tough to extract these unique features from the input image of inter-class and intra-class of animal datasets that are almost identical pattern across the vast population [57]. The usefulness of high variability in patterns of intra-class of phenotypic appearances of species provides a method to recognise individuals [22, 39, 40, 58, 59].

3 Major impact of visual animal biometrics on field ecology

Several pioneering types of research and studies have shown the potential capability of visual animal biometric systems. The visual animal biometric system is efficiently applied in the various field projects for the quick localisations of species in spatio-temporal space from the remote field ecology, remote audio-visual recordings. For significantly escalating number of uniquely recognisable or detectable the individual species than they can be tracked and monitored over time and space [60–63]. For better monitoring and tracking of species in field ecology, computer vision and pattern recognition algorithms are well-developed for the help of animal biometrics system for recognising different species such as African apes, chimpanzees and gorillas using face detection algorithms [60] (shown in Fig. 3). Visual animal biometrics performed the classification of African apes, chimpanzees and gorillas and yields 92–97% of recognition accuracy (e.g. recognition accuracy) under normal condition [42]. Both the image quality and clear visibility of face images of chimpanzees have a significant dependency to perform the correct classification and achieve a better recognition rate. However, classification rates of different species degrade if image of species or individuals does not have good quality or clearly visible, therefore, they cannot be recognised easily by facial detection algorithms.

Fig. 3 presents the identification of different species in field ecology from the captured video. The face images of animal are captured by various camera traps or surveillance camera (video) in ecology field. The face image of chimpanzee and gorilla has been recognised successful and depicted in bounding boxes and highlighted in green frames.

Table 1 A literature review of visual animal biometric algorithms

Ref.	Species	Database	Modalities	Algorithms	Features	Performance measure
[8]	zebra[a]	1722 images	texture patches	texton	SIFT	recognition rates (82% for all), 89.30% for zebras, 55.6% for tigers and 59.7% for giraffe
[12]	animal	4000 images (30 classes)	face	graph-cut + PNN	Fourier transform	82.70%
[38]	elephant	332 images ×268 subjects	ear nicks	shape features	shape and global matching	92% (recognition rate)
[39]	zebra	120 images	coat pattern	stripe-codes, CO-1+	joint strips of coat pattern	85%
[40]	chimpanzees	6526 images[b]	face	computer vision	pixel intensity	26.36% FRR (for Chimp Tai) and 21.29% FRR (Chimp Zoo)
[37]	whale shark	6064 images	spot pattern	pattern recognition	spot pointing features	81%
[6, 41]	humpback whale	24,428 images	marks or scars	pattern matching	black and white pigment pattern	56%
[42]	ape + chimpanzee+ gorilla	15,000 images	face	local features	LBP	92.3%
[43]	tiger + Ponda	14,379 images	head face	HOOG	texture features dynamic programming	92%
[44]	Otago skink	6000 images	visual	geometry feature	LBP+SIFT+PCA	92%
[45]	pet animal (dog)	3000 facial images	face	facial features	PCA+LDA+ICA texture features	96%
[46]	animals	12 images	animals	ECG feature	RFID	ECG-features electrocardiogram, (arterial blood pressure)

ECOCEAN: Whale Shark Photo-identification Library (http://www.whaleshark.org/).

a

Zebra = (zebras+ tigers + giraffes + other images), LBP = local binary pattern, LDA = linear discriminant analysis, PCA = principal component analysis, SIFT= scale invariant feature transform, PNN = probabilistic neural network classification model, FRR = false reject rate, ECG = electrocardiography signal.

b

http://www.saisbeco.com, HOOG = Histogram of Oriented Gradient.

Fig. 3 *Illustrates the different species and individual animals are identified from videos by using visual animal biometrics-based recognition systems [2]*

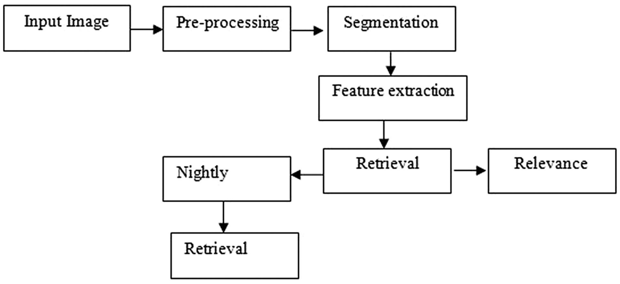


Fig. 4 *Illustrates the various components of SLOOP animal identification systems. The workflow presents an interaction between the various user and systems*

In the case of other animals as well as one gorilla is shown in the red frame of the video are not recognised because their head is not able to be identified correctly. The manual processing techniques take more processing time for filtering chimpanzee and gorilla footage, which is greater in comparison with animal biometric-based recognition system. For example, chimpanzee and gorilla habitat use overlap [2, 64–66]. The major contributions of capturing large amounts of video footage database play important roles in regularly processing for depth studies across field ecology [65–69], biology and genomes. Visual animal biometrics has provided an enormous capacity for voluminous amounts of video footage of species in ecological fields.

4 Visual animal biometric system

In this section, visual animal biometrics presents animal identification systems for recognition of species or individuals.

4.1 SLOOP: a pattern engine for animal recognition

SLOOP is pattern retrieval-based animal biometric system for individual identification in the current state-of-the-art based approaches. It retrieves the discriminatory features (information) from the morphological image pattern and biometric characteristics of species or different for the recognition purposes (source: https://sloop.mit.edu) [1]. The SLOOP animal biometric system uses the fundamental concept of cloud computing, machine learning [22] and crowdsourcing [21] to significantly improve the study of animal monitoring, movement, detection and representation of phenotypic appearances, morphological image pattern and their behaviour analysis [70].

The working block diagram of the SLOOP animal biometric system is shown in Fig. 4. It requires uploading the images of different species or individual and its metadata as necessary input images for recognition purpose. The uploaded input images are pre-processed for extraction of feature and matching process [1, 68, 69].

Fig. 5 shows the examples of preprocessing steps for identification of various species. The approach is chosen for a particular species dataset depend on, the essential characteristics of that used datasets and the massive availability of human resources.

The specularity removal algorithm has been incorporated within Sloop as the animal identification system. The working of specularity removal using different algorithms is shown for Fowler′s toad in Fig. 5 A.

The working model of SLOOP system marks a few specular and normal regions of individual species based on their photos. Based on input images, SLOOP system removes the detected specular spots with discriminatory information from original regions of species to seamless in-fill. Sloop retrieval based identification system applies the mean-shift based, SVM classification models and segmentation methods using graph-cut techniques based on color-texture features of species or individual animal. The working of SLOOP system for species identification is shown in Fig. 5 (B).

Fig. 5 (C, D) illustrates the working of SLOOP system to retrieval of biometric characteristics from marbled salamanders, skinks and geckos species.

SLOOP system also applied to other species. The SLOOP system performs the segmentation algorithms to find the region of interest (ROI) patch selection around fiducial points with rotation, affine or spline-based normalization as shown in Fig. 5 (E). Finally, SLOOP system can be applied to extract the Lagrangian features whale shark. The spot pattern and Lagrangian features both marked and automatically detected. These are invariant feature detectors for matching, as shown in Fig. 5 (F).

Fig. 5 A depicts the pre-processing of various species, the specularity removal algorithms with SLOOP recognition systems in presenting for fowlers toad species. By applying the specularity removal algorithm, some regions are marked for identification. As mentioned in [1], SLOOP system has mean shift-based support vector machine (SVM) classification techniques and graph cut segmentation approach based on the technique of colour texture feature extraction shown in Fig. 5*B*. Figs. 5*C* and *D* show a conventional mode of rectification for deformation species with substantial bilateral symmetry as marble salamander's kinks' and focus is to mark a preferred axis of symmetry. In the skins, for example a few points mark the patches and their orientations (see Fig. 5*E*) which are rectified and used for matching. Finally, Lagrangian features [71] are extracted by SLOOP system for the detection of whale shark (shown in Fig. 5*F*.

4.2 ECOCEAN whale shark identification system

Currently, visual animal biometrics has gained more proliferations due to a variety of application and use in the recognition of various species across the world. Visual animal biometric systems have applied to considerably growing the quantity of uniquely spotting species or individuals based on ECOCEAN Whale Shark Photographic-identification Library [25, 72]. For the preparation of Whale Shark Photographic-Identification Library database, a joint endeavour of more than 3500 multidisciplinary researchers, active volunteers, engineers, biologists and scientists are involved. Their

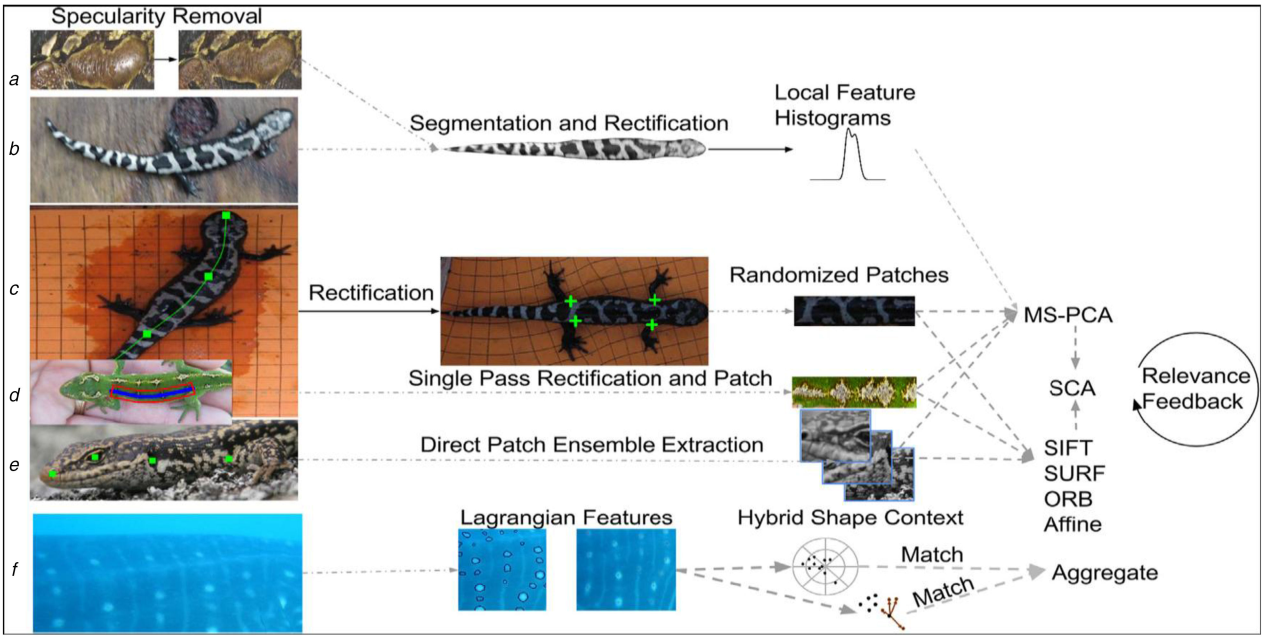


Fig. 5 *Illustrates the identification of different species using SLOOP animal identification systems [1]*

a *b* *c*

Fig. 6 *illustrates the identification of whale shark species*
(A) Acquisition of whale shark images, ***(B)*** Spot point features (Lagrangian features) is detected and ***(C)*** Illustrates the localisation of Lagrangian feature points and extraction extracted from the whale shark photo-identification library [72]

contributions are valuable for the acquisition of more than 43,000 images of whale sharks from more than 3800 individual subjects (whale sharks) [2, 28] (source: http://www.whaleshark.org/). The identification of whale shark based on their Lagrangian features is shown in Fig. 6.

5 Fundamental requirements for promising applications

The essential requirements of applications, visual animal biometrics have pre-requisites before beginning the design and development of recognition systems for a precise use of the study of animal populations and analysis [73]. Therefore, it can be beneficial to reflect on following the most important fundamental requirements of promising criteria for evaluating its success, prospective weaknesses, expected experimental results and performance measures (accuracy) and robustness under different variations in field conditions mentioned as follows:

i. The basic need is to find out the degree of differentiation between the various species classes of interest (i.e. group, species, individuals, behaviour and their morphological characteristics). It can be defined fundamentally for automated classification systems and how such systems will work based on inter-class and intra-class variances of species populations. These procedures establish whether the feature variants of the class of interest classified with high probability and minimum misclassification rate.
ii. As a result, interdisciplinary researchers, scientists and various research committees try to mitigate the effect of covariates challenges of the face image of animals using computer vision approaches [74–76]. The effects of covariates are significant problems for representation, detection and classification of species or individuals. The biggest challenges of automatic animal recognition systems classified into six categories: (i) low illumination, (ii) poor image quality, (iii) movement and different expression, (iv) body posture (pose), (v) occlusion and (vi) disguise (e.g. covering and non-covering of body parts during vegetation) [20].
iii. For the best representation, recognition and classification of audio-visual feature data (source) and extracted features, the exposure of features sets of the interest of such source data will determine how well classification and recognition algorithms can evaluate the performance measures.
iv. For example, this includes restricting geographic ranges of species populations for interest that might help to mitigate the possible classes of interest significantly; the combination of predictable visitation, as well as activity patterns and different features.
v. The modern technologies, software packages and tools used for audio-visual recordings can discover how well a system will do in the long-term usages. The dynamic changes (e.g. environmental challenges, weather conditions etc.) can set back stability of hardware systems due to the changing environmental conditions; user friendliness, including natural use, software security. The utility of globally accepted data formats and secure transfer of data over different geographical locations using networks can provide motivation to research and improve the acceptance by practitioners.

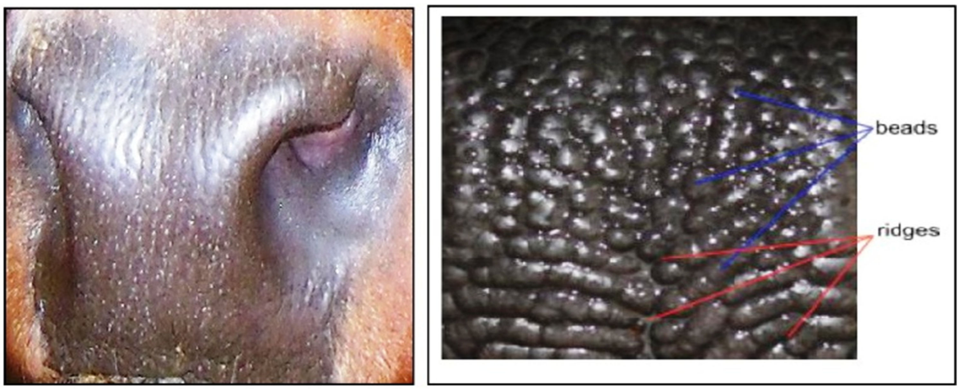


Fig. 7 *Illustrates the original muzzle point images and extraction of beads and ridges pattern from the muzzle image of cattle*

6 Classical animal recognition methodology

The recognition approaches of animals have gained more advancement due to a variety of applications such as registration and traceability of livestock animals [54]. The animal identification plays a significant role for registration and traceability purposes. The registration process of animals would thwart efforts for manipulation, duplication and fraudulent of markings, such as ear tags and traceability process provides complete information regarding food, feed, and health monitoring.

The classical animal recognition methodologies are divided into several groups, namely (i) permanent identification methodology (PIM), (ii) semi-permanent identification methodology (SIM) and (iii) temporary identification methodology (TIM). The classical animal recognition approaches are shown in Table 2.

Johnston and Edwards [77] studied that ear-tags damages the cattle's ear. The labelled ear-tags can be lost easily. Moreover, ear-tags can also be eventually damaged. Thus, ear of livestock animal gradually corrupted due to long-term usages [78, 79]. Therefore, classical animal recognition methodologies fail to provide the competent level of security, health monitoring and tracking of livestock cattle [80, 81].

Besides that, all categories of classical animal identification techniques, the artificial marking techniques (ear-tags, embedded microchips, freeze-branding and hot ironing) are duplicated, fraudulent and forged the labelled ear-tags. Therefore, artificial marking techniques are unable to identify and verify the false insurance claim and manipulation of cattle. Due to the failures of the classical animal recognition techniques are explored as alternative approaches for identification of livestock.

In the available literature, it has shown that dermatoglyphics (e.g. ridges, granula and vibrissae) of muzzle point image pattern from various livestock breeds (races) are mostly differences. The recognition of muzzle point images is similar to the minutiae points recognition of human's fingerprint [48, 49, 82].

The main attribute of muzzle point image can be grouped into two important patterns known as bead pattern and ridge pattern (shown in Figs. 7 and 8, respectively). The bead patterns are irregular structures and its shape is similar to islands. The ridge pattern is a regular structural pattern and its shape is like rivers. It separates the bead pattern. Therefore, muzzle point pattern of cattle is a suitable and primary animal biometric identifier for recognising the individual cattle [48, 49, 81, 83, 84]. Only few researches have been done so far and proven that muzzle point can be used for cattle recognition to provide better solutions to such major problems in the classical animal recognition approaches by applying the muzzle point pattern of cattle [85–91]. The muzzle point image pattern is classified into two primary attributes known as beads and ridges, shown in Figs. 7 and 8, respectively. The beads are unique arrangements which shaped is comparable to the islands; while ridges of muzzle point pattern are the structure which formed like rivers, and it separates the beads.

Barry *et al.* [92] proposed the approach for recognition of beef cattle using beads features. However, they have had 241 false non-match rates over 560 genuine acceptance rate and 5197 false matches over 12,160 for the imposter matching. The authors [93, 94] proposed a method to recognise the cattle using their facial images. In [49], the authors proposed the approach for cattle identification by refinement in SIFT and speeded up robust feature (SURF)-based descriptor [79, 83] approach for matching of the score of muzzle print images.

7 Opportunities, issues and challenges

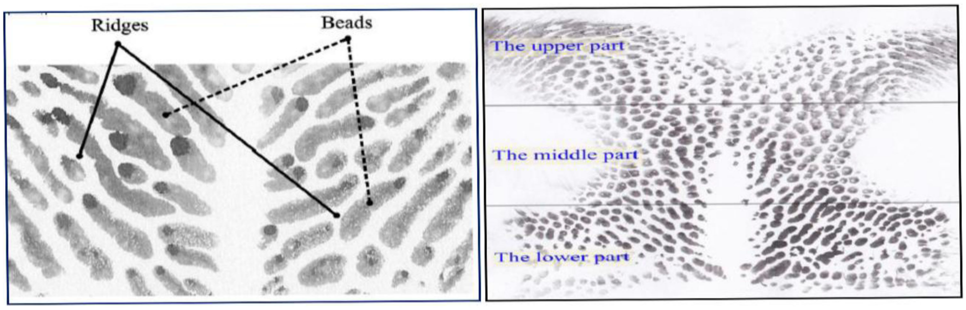
Visual animal biometrics has given a major prospective to support the documentation, filtering and indexation of representative data, audio-visual recorded data and taxonomic content generated in many ecological and evolutionary studies [73]. In modern technologies, currently used devices have been applied for the acquisition of ecological data, such as hand handle sensor devices (audio-video devices), camera traps and acoustic recording equipment [95] and different sensors carried by aerial vehicles exploited for document observations [96–99]. The various sensor and intelligent devices produce massive quantities of video, audio-visual recording data and captured images of species that might frequently be at the limit of what may be analysed by processed manually as repetitive tasks [30, 39, 40, 73, 96] and produced potentially bias observations [100].

The appropriate time is needed to sift through the environmental and ecological data that may be higher than the

Table 2 Classification of classical animal identification methodology

Identification/attribute	PIM				SIM		TIM	
	Tattoo	Microchip	Ear tip	Freeze brand	ID collar	Ear tags	Sketching (paint/dye)	RFID
reliability	M	VH	H	VH	L	L	L	VL
cost	M	VH	L	M	L	L	VL	VL
visibility	VL	NA	M	H	VH	VH	VH	NA
longevity	H	VH	VH	H	L	L	VL	L
risk of harm	L	VL	M	L	HL	VH	VL	VL
accuracy	H	VH	NA	L	H	L	VL	H
uniqueness	H	VH	NA	L	H	M	VL	VH
DBR	H	VH	NA	L	L	M	NA	VH

SIM = semi-permanent identification method, PIM = permanent identification method, TIM = temporary identification method, DBR = database required, NA = not available, L = low, M = medium, H = high, VH = very high, VL = very low.



a b

Fig. 8 *Muzzle point image pattern is classified into two primary attributes known as beads and ridges*
(a) Beads and ridges of the muzzle pattern lifted on paper and ***(b)*** Upper part, middle part and lower part of a muzzle pattern image

actual recording time. Currently, animal biometric systems provide greater bits of help by offering the significant and discriminatory information on the actual occurrences of particular species, morphological patterns of interest in a very less amount of time or a fragment of used them. The recognition and matching process of morphological texture [101] pattern for different animal identification in a quantifiable way is primary algorithmic challenges in visual animal biometrics. Moreover, major challenges are how to capture the structural complexity that exhibited by of species using computer vision models since of species actively change its shape pose, and body surfaces of species reflect differently under varying lighting conditions [102, 103].

Various detectors have developed for the matching of image templates (e.g. morphological pattern based templates) and take one prototypical instance of overall visual appearances of species. These techniques have given the efficient representation of various pictures of the species class of interest that can represent using images of a particular type of insects [104] and that stand for the whole species. Although it is easy to generate and straightforward to match against stored templates in the database, it caters low recognition accuracy when detecting animals under natural conditions. Recently, survey report on different population and monitoring studies increasingly exploit the multimedia technologies such as sensors, camera traps and passive audio-recording devices [96]. For better ecological monitoring, animal biometric systems have the potential contribution to mitigating significantly the time spent analysing the recorded data from various sensors, camera traps and audio-visual recording devices.

Although, various certain ecological monitoring studies have presented the perspective of integrating the animal biometric system into such systems for the estimation of population sizes, structure and residence time for whale shark using collaborative photo-identification systems and matching systems [19, 105]. Considerable research work remains to provide integration to the output of visual animal biometric fully into traditional statistical framework and models for the development of standardised and benchmarking system results. In a similar way, assessments of biodiversity are increasingly conducted to recorded document and compute the major impacts of human activities and study questions on ecology community are showed potential fields of applications [106–108].

7.1 Research communities, tools and data sharing

Visual animal biometrics is still in their infancy and has given a lot of opportunities to researchers, scientists, ecologist, biologists and experts in this open research field. It provided a platform of the extremely interdisciplinary field that collects various inputs from different multidiscipline fields to design and develop an automatic, non-invasive, accurate, cost-effective, robust and widely applicable well-developed tools and approaches. Thus, there are some fundamental requirements for the design and development of a research platform where numerous researchers can perform the better analysis based on successful collaborations and sharing of expertise among different members of the various scientific communities throughout the world.

For sharing of expertises, tools, various datasets and communication can play a vital role in depth researches, analysis and sharing of valuable knowledge for providing efficient solutions for the different complex problems. In this manner, scientists and several engineers will be required to make information what a recognition system can represent, detect and recognise the various species or individuals biometric characteristics. These procedures will provide the most efficient way for the generation of tags and morphological pattern metadata automatically. The shared expertise and knowledge can reflect clear procedures about automated audio-visual techniques, responsible for the processing of the ecological data, collection, and its interpretation when processing technology have shown in highly repetitive tasks [73]. It can be completed faster by computational systems such as, computers and mathematical models, however; human observations are more expensive as compared to automatic monitoring and tracking of species.

Although, human observations consume more time to perform processing of ecological data sets. However, processing techniques need to be completely implemented and clearly communicated that these things increases in quantity can, in turn, be offset by various uncertainties in the experimental results as well as in processed data. An example can also understand it; recognition systems recognised any individual or species from stored template database (shown in Fig. 2) using matching algorithms. Table 3 illustrates the existing animal biometric system, research communities, tools and data sharing for the ecologists, biologist, new user and as well new research communities.

7.2 Technical challenges

Visual animal biometrics exists with a variety of broad spectrum of approaches to the input data acquisition, detection of the species, matching algorithms, storage of different template generation and various interfacing, as shown in Fig. 2. The diversity of approaches, tools, and technology often provide opportunities and their transferability across different studies, paradoxically one of the primary objectives of visual animal biometric systems. Introducing a more modular system designs and recognising of conventional methodologies and techniques perform some modifications to individual studies is a critical objective to provide efficient solutions in a more generic form and cheaper to generate and maintain.

Such efforts or move towards this goal will help to provide a better standardisation in the ecological fields and motivates it for wider application in distinctive disciplines. In general, the basic algorithmic challenge is remaining in coping with poor lighting conditions, occlusion, pose variations, reflectance from their body surfaces, deformation in complex organs and require to label the annotated manually the massive image datasets [23, 98, 99]. The camera traps produce the high temporal resolution-based videos; still, camera traps regularly comprise only a small area of ecological fields. Such scenarios can be practiced to evaluate the population density. To make some modifications in Capture–Mark–Recapture techniques for the solving uncertain sighting data beyond the current state-of-the-art based methodology is also likely to attract the swelling interest [124–126]. To build the most efficient and robust systems dictate careful consideration of workflows [37], so as to provide a continuous better integration of human and machine capabilities.

8 Recognition and monitoring techniques

Visual animal biometrics is an emerging research field of computer vision, pattern recognition, and animal behavioural analysis. It is promising areas of broad applications to cater the assistance for filtering, indexing and processing of biological, ecological (e.g. audio-visual content) data. The monitoring and population analysis are significant challenges for species or individual animal in their natural habitats.

In this section, efficient animal monitoring and recognition methods are illustrated in detail for identification, representation, detection of species and its appearances, behaviours analysis, morphological image pattern and biometric characteristics. The detection and description of morphological pattern and biometric characteristics of species are classified into several categories, namely (i) representation of species morphological features using visual models, (ii) texture feature based descriptor approaches and (iii) species appearance based detection and image approach. The brief descriptions of recognition methods are given in the following subsection.

8.1 Representation and detection of morphological features

Representing and recognition of morphological image pattern of species in a quantifiable way are a central algorithmic challenge in computer vision, pattern recognition, and animal biometrics. These significant problems are how to capture the image of animal body pattern (configurable landmarks, coat pattern) and describe these patterns using computer vision approaches and visual models. Since species dynamically change their body shape and pose, different reflection from their body surfaces exhibited under constant lighting conditions (illumination conditions) and occlusion of animals. Individual animals frequently become visible as partially hidden by vegetation. To solve these major problems, computer graphic-based models also are applied to represent the morphological features of species for monitoring and tracking of the animal. However, computer graphical and visual models based are unable to demonstrate the compact representation and detection of species. These models do not allow a substantial integration between them and captured input data, such as morphological image pattern, biometric data or video data [123].

For the represent and detection of species using visual models, the key difficulties are illustrated as follows: suppose, a visual model and set of morphological images given, how can one decide to choose the discriminatory features from the pictures for class discrimination of species. How to learn the models by segmenting the image pattern into the region of interests (area) and computation of relevant image features for better representation of morphological features in the feature space with parameterisation of the visual model it means that what is the actual pose of the animal.

In contrast, advanced representations capture dynamics in deformable models. These models present the observations by integration of discriminatory information from the different parts of the animal body (e.g. segmentation of movable limbs of the animal body) and learning the flexible links between limbs. Based on current state-of-the-art animal representation and detecting approaches, large training data sets needed to maintain the thousands of manually annotated images of animals and significant computational resources (e.g. system level and hardware level resources). These resources are required to build the computer graphics and visual models for better representation and recognition of species. The visual animal biometrics recently provided excellent current alternatives. Such as spline fitting [29, 59] of captured images, diffeomorphic models [74] and shape contexts based represent models [47, 104] for detecting and representation of the appearance of species. However, these models consume more time for pre-processing and extraction of morphological image features. Therefore, computer visions based shaped are computationally more expensive.

Table 3 Examples of existing animal biometric systems for species and individual identification

Projects	Species	Modality	Resources	Ref.
1. SLOOP[a]	whale sharks and others[b]	visual	http://ecovision.mit.edu/~sloop/SloopProject/SLOOP.html	[1]
2. RBT+ACONE	birds	visual	http://rbt.cse.tamu.edu	[24]
3. ECOCEAN	whale sharks	visual	http://www.whaleshark.org	[25]
4. APRS	penguins	visual	http://www.penguinid.com	[50, 109]
5. Conservation research	animal	visual	http://www.conservationresearch.co.uk	[51]
6. Stripes potter	zebra	visual	http://code.google.com/p/stripespotter	[39]
7. White shark	white shark	visual	http://www.marinecsi.org/white-shark/	[41]
8. SAISBECO	ape	visual	http://www.saisbeco.de	[42]
9. Database of Asian Elephant	elephants	visual	http://www.asianelephant.net/index.html	[110]
10. Cheetah Database System	cheetah	visual	http://cheetahdatabase.sourceforge.net	[111]
11. RhODIS	rhino	DNA	http://rhodis.co.za/	[112]
12. Serengeti Lion Project	African lions	visual	http://www.snapshotserengeti.org	[113]
13. Shepherd Project	shepherd	visual	http://www.ecoceanusa.org/shepherd	[114]
14. iBATsID	bat specie	acoustic	https://sites.google.com/site/ibatsresources/home	[115]
15. Discover Life	species	visual	http://www.discoverlife.org/	[116, 117]
16. Shark Identification	whale shark	visual	http://sharkidnetwork.com/about	[118]
17. PanTHERIA	mammalian	visual	http://esapubs.org/archive/ecol/E090/184/default.htm	[119]
18. PAM	humpback whales	acoustic	http://stellwagen.noaa.gov/science/ passive_acoustics_current.html	[120]
19. BEEtag-tracking system	animal	visual	http://biorxiv.org/content/early/2015/06/03/020347	[121]
20. CSIRO	wildlife collection wildlife species sound archive		http://www.csiro.au/OrganisationStructure/Divisions/Ecosystem-Sciences/ANWC- Sound-Archive	[122]
21. Fish datasets	fish	visual	http://groups.inf.ed.ac.uk/f4k/GROUNDTRUTH/BEHAVIOR/	[123]

a

SLOOP = SLOOP: photographic animal ID system.

b

Others = salamanders, grand skinks, Otago skinks, Geckos, visual features = appearance (patches, local features), geometry (scale-cascaded alignment).

8.2 Texture feature-based descriptor approaches

Texture feature-based descriptor is a substantially well-defined function. The descriptors encode the input image region (region of interest) into a corresponding set of feature vectors. The size of descriptor window is defined as ($M \times N$) where M and N are the number of rows and columns, respectively. The research communities in computer vision and pattern recognition have addressed the problem of animal identification and monitoring in their habitats by developing automatic texture feature-based descriptor approaches for better representation of extracted features in the feature space. The descriptors algorithms extract the surface feature and represent the features in the feature space by encoding of monotonic grey scale animal images for true representation. Based on the computed texture features, animal biometrics based recognition systems recognise species or individual by representing and matching features with the stored image database efficiently.

For the recognition of animal using tiny or rigid regions of body surface of animal, in such case, small region of interests (areas) of animal skin, frequently demonstrates the minimal variance rather than entire animal body. In this case, sets of local descriptors [39, 51], such as SIFT, dense-SIFT, local binary pattern (LBP), SURF[52] descriptor algorithms have been applied to recognise individual specie using small regions features effectively to represent morphological image pattern and appearance of animals.

SIFT is a texture descriptor-based recognition method. SIFT extract the discriminatory key points as essential features of detected morphological image and compute the feature descriptors and describe and represent the local features in the images. The detected SIFT key points initially extracted from the animal images [1] and these key points are stored in a biometric database. An animal is recognised in new testing images by individually comparing each feature vector from the new image to this database and finding corresponding matching features based on the Euclidean distance of their extracted feature vectors.

Promising applications of SIFT methods are mainly recognition of animals, stitching of morphological images, detection of keypoints as landmarks on animal body, three-dimensional (3D) modelling of species features for recognition, video tracking, individual recognition and monitoring of wildlife species. The texture descriptor-based algorithms provide the effective and automatic recognition of species where pose and lighting condition do not vary. Therefore, texture descriptor-based algorithms extract the local texture features from the animal images for stable recognition of rigid surface areas of species [53].

In the similar direction, rotation invariant feature transformation (RIFT) is also a feature descriptor technique. RIFT is a rotation-invariant generalisation of SIFT techniques. The descriptor of RIF constructed with circular normalised image patches. The image patches are divided into concentric rings of equal width. Within each ring, a gradient orientation histogram is calculated for the recognition of species and individual under clutter, low illumination, and partial occlusion.

Various species (e.g. insects) are identified based on extracted their distinctive local body features and local gradient distributions of the body surface. The visual animal biometric systems have provided the gradient histograms based approaches for modelling and learning strategies of extracting features for representation and identification of species. The identification system performs the matching of test images of the animal with stored morphological image pattern database using similarity matching and k-D tree data structure for sorting the discriminatory feature vector for the recognition of animal.

For animal classification, feature-based learning methods along with an LBP-texture descriptor algorithm applied to classify the histogram bins using SVM and other machine learning approaches. For the identification of tortoise using local features, LBP texture descriptor method is applied for representation of texture features of tortoise is shown in Fig. 2. Fig. 2 shows the extraction of interest points from the images of tortoise. After extraction (e.g. pols features of tortoise) features, SVM classification technique is applied to classify the tortoise spices based on extracted pols features (see Fig. 2).

Extensive applications of texture descriptor algorithms range extensively from classification of insect species [54] to identification of only reptiles [55]. However, global information (feature) has not exploited by these local texture descriptors which disregard the body structure or observation viewpoint. Therefore, in such cases where variations are dynamic changes in animal appearances, the morphological image pattern, partial clutter, occlusion, poor image quality, shadows, or glares cannot be circumvented; texture feature-based descriptor algorithms fails to provide the compact representation of features or morphological information of species in the feature space.

In the current state-of-the-art based concept of Internet of Things (IOT) also played a vital role in monitoring and tracking of wildlife animal. For ecologists, it is difficult to understand the strong reaction of wild animals to critical environmental changes. The IOT-based capable devices and sensors technologies applied to measure wildlife and environmental parameters and provide accurate, cost-effective, real-time and widespread data for identification, tracking, monitoring, research and conservation of wildlife [127]. Detail illustration of animal biometric-based approaches for species recognition (Table 4).

Localisation and encoding of joint strips (e.g. joint strips or junction) in coat pattern (for a zebra), spot patterning of the whale, and penguin, keypoint detection in SIFT features (e.g. for a Masai giraffe) and ear-nick pattern of elephant are discriminatory biometric features for the recognition of individual animal. Visual animal biometric based systems are also providing the helps in the filtering the captured datasets and indexing of audio-visual information that is progressively more produced in many ecological and evolutionary studies using computer vision and pattern recognition for individual. The visual recognition of individual animal based on their biometric and morphological characteristics is shown in Table 5.

Table 5 illustrates the modelling and machine learning strategies for training the visual animal recognition system and learning models using extracted features. In Table 5, promising applications of individual animal identification using pattern recognition techniques is highlighted. Also, these biometric and morphological image patterns are represented using various computer vision models, such as active appearance models, SIFT local feature-based models, local and global feature-based representation models.

In this paper, learning model and feature representation techniques for recognition and detection of species behaviours or individuals are given in Table 6. Numerous learning models and recognition algorithms have been developed to assist the preclinical research on the behavioural of different species or individual animals. In the traditional, animal behaviours are measured manually. It is slow and laborious. Besides, human observers always fail to produce the experimental results of behaviour analysis since the decision is subjective. The behavioural evaluations are too fast and human observers can miss due to flagging attention.

To overcome these limitations, computer vision and animal biometrics have provided automatic systems, machine learning strategies for representation of analysing social behaviours of animals. These models help biologists, ecologists and several new practitioners and multidisciplinary researchers to perform better results, save considerable time and efforts.

The computer vision and animal biometrics models perform the matching of similar activities by similarity matching of between query test images and train images. For the recognition and analysis of mice behaviour, home cage activities are analysed. For the analysis of mice behaviour, motion and different activities are captured in spatio-temporal domain (video) and this behaviour is classified by SVM.

The learning models fit the contours of different insects or files and applied for behaviour analysis and representation. These models efficiently detect and extract the features from the single frame (a set of images) (video). Then detection results obtained from the trajectories and classification models, such random forest (RF), SVM, AdaBoost and K-NN classification models are applied to classify the behaviours of different species. The models and machine learning algorithms represent the behaviours by tracking and detection of the species behaviours with high-performance measure (e.g. recall rate, recognition accuracy) in real-time scenario.

9 Visual animal biometrics: the current state-of-the-art

The current state-of-the-art of based visual animal biometric system is shown in Fig. 9. Fig. 9 presents a flowchart of the current state-of-the-art based methodologies for animal recognition. It also illustrates the acquisition of high-quality ecological data (input data), detection of morphological pattern, phenotypic appearances, matching of image pattern templates, large storage capacity and interfacing the relevant outputs among different research communities for better study and analysis. The working of visual animal biometrics is divided into two main components, namely (i) training phase and (ii) testing phase. For the training phase, the system takes biometric data from different study site using various sensors (camera) known as acquisition phase (Fig. 10).

The discriminative morphological image pattern and texture features are extracted from the captured input images using different computer vision, pattern recognition, and machine learning approaches. The approaches are mainly principal component analysis (PCA) [166, 167], linear discriminant analysis (LDA) [167], independent component analysis (ICA) [168] and other variants. The texture descriptor approaches are LBP [169, 170], SURF and SIFT [171] technique to extract the features for training the proposed framework for recognition of different species or individuals and analysis their behaviours.

In the testing phase, unknown test images are compared feature sets (templates) against the feature set(s) stored in the database in the form of the template and executes an action based on the result of the similarity based comparison for matching purpose [172–174]. The proposed visual animal biometric system plays a major role in multiple disciplines (e.g. biometrics, biography, ecology, population, computer vision and behavioural research). Further, visual animal biometric-based recognition system make use of both the variety and uniqueness of vocalisations, coat patterns, body dynamics and morphological image pattern as unique and suitable biometric characteristics [2]. The coat pattern of zebra, penguin, spot points of tiger and muzzle point image pattern [48, 49] of different animals (cattle) are similar to minutia point's recognition in human fingerprints [175].

Table 4 Detail illustration of computer vision and pattern recognition-based approaches for species recognition

Type of species	Identification	Computer vision and pattern recognition techniques			Annotation requirements	Ref.
		Modelling and learning algorithms	Model representation	Matching and localisation techniques		
Chimpanzee, gorilla, monkey	**Facial images** (rigid spatial decomposition) and (representation of facial features)	• AdaBoost classifiers• indexing• look-up tables	• bounded box-based features• census features• histogram of oriented gradient (HOG) features	• cascaded rules• sliding windows based algorithms	• annotation of facial region using bounding box	[42]
Cat, tiger, lion, Panda, fox, cheetah	**Head counting-based feature of animal** (deformable decomposition of head shape and texture)	• boosting• SVM classification	• box bounding features• census features• HOOG features	• dual approach• sliding windows	• annotation of head and facial features	[43, 128, 129]
Pet animal (cat, dog)	**Shape and texture features, facial, body and nose print (for cat)** (deformable decomposition of face features and uniform body texture)	• sparse representation• latent SVM• colour histograms, Gabor• descriptor model	• geometric model• active appearance models• deformable model• HOG features• pixel colour	• descriptors of part localisation• matching• sliding windows• Grab-cut• segment compactness	• facial region, annotation using bounding box	[128–134]
Various species of insect Drosophila melanogaster	local pattern and texture features	• deep neural network• maximum correntropy criterion	• stacked de-noising auto encoder• pixel intensity of images	• correntropy matching and second-order statistics)	• not required	[135]
Musca domestica (flies)	patches and texture pattern	• stacked de-noise-auto encoder• SVM	• pixel intensity of images,• deep learning	• similarity matching correntropy matching	• not required	
scorpions – Centruroides limpidus and Centruroides noxius	shape features	• image processing techniques• ANN	• texture feature (aspect ratio, rectangularity, compactness, roundness, solidity and eccentricity)	• similarity matching• regression tree• RF classifiers	• not required	[136]
Mosquitoes	**Audio feature** (features using speech and audio)	• feature-based classification models	• temporal and spectral representations	Similarity-based Classification	• not required	[137]
other insect species	Distinctive **local body features** (local gradient distributions)	• gradient histograms	• SIFT• local feature concatenated histograms	• scale-space extrema• k-D tree matching	• not required	[53]

10 Conclusion and future directions

This paper presents a comprehensive review of the broad spectrum of quantified approaches for representing, recognising, classify morphological and biometric characteristics of species, individuals and behaviour analysis. Visual animal biometrics is an emerging research field on the edge of supplying efficient, robust methodologies, recognition models (actual appearance) and tools. The efficiently developed algorithms, systems, and tools have been completely used to collect and process the phenotypic appearance and morphological features in the broad spectrum of standardised approaches and for large applications.

There are numerous challenges stay in front of design and develop animal biometrics field into a broadly accepted and used widely in the applied subjects. There is a still greatest challenge due to the communication gap, sharing of expertises, knowledge and efficient tools between the different multidiscipline researchers and research communities that involved their contributions for the development of better research platforms in animal biometrics.

Thrilling ideas include the automatic recognition systems such as robot systems and drones in animal biometric systems that actively try to find data by traversing the different habitat to enhance both the quality and quantity of captured data from various sensors and artificial intelligence-based learning systems and data mining. It acclimatises better to highly unpredictable and dynamic morphological pattern of species, continuously improving on system capabilities for recognition. Visual animal biometric systems have various potential applications in a wide range of studies. Therefore, such systems have shown their major capability and potential in the new coming research field such as genomics and phenomics. It is essential keys for sharing and provides better linkages of phenotype appearance characteristics of all organisms to other organisational levels of life. Therefore, to integrate all closely interacting biological processes those are only responsible for the constitution of genetic and physiological characteristics of an organism with the dynamics of populations or to the interactions of communities.

Visual animal biometric systems provide a future perspective for the innovative new breed of scientists, researchers, biologically knowledgeable engineers and technically potential biologists to solve the problem of complexities during designing of systems.

Table 4 Continued

Type of species	Identification	Computer vision and pattern recognition techniques			Annotation requirements	Ref.
		Modelling and learning algorithms	Model representation	Matching and localisation techniques		
Tephritidae (fruit fly)	local body features **Texture feature**	• SVM• local soft coding (LSoft)• discriminative LSoft method	• SIFT features• patches (densely sampled from each image)	• sparse coding• spatial pyramid matching	• not required	[54, 138]
birds (NABirds, dataset containing 48,562 images)	**colour feature**	• machine learning• MTurkers	• pixel intensity of bird images	• machine learning (SVM) classification	• body colour annotation using bounding boxes	[139], [177], [180], [181], [183]
	image pixel intensity features	• deep convolution neural network (CNN)• SVM	• CNNs,• FCNs• SuperParsing,• AdaBoost, with Haar-like feature	• AdaBoost with Haar-like feature	• not required	[140]
Bird species	**image feature (pixel intensity)**	• multimodal recognition algorithm	• SIFT• body tracking algorithm	• SIFT keypoint• Similarity matching of keypoints	• not required	[141]
Oriole bird (Baltimore oriole (Icterus galbula)	**colour feature**	• deep learning• CNN feature baselines	• LDA• entropy-rank curve	• grab-cut mask• fine-tuned CNN features	• training the model with annotation colour-based features using bounding box	[142, 143]
African Penguins Spheniscus demersus South Polar Skuas and Adélie penguins	**Chest patterns (body)** natural markings in the chest plumage	• computer vision models• features Procrustes + mean square error• regression models	• chest pattern Features	• matching software• cascaded rules	• training the labelled key points on chest body as annotation	[58, 144]
Quadrupeds	**Gait motion** (Spatio-temporal configuration of body part of animal	• PCA• LDA• normalised convolution deep learning, SVM, KNN	• principal component of motion fields• KNN search	• sparse• Kanade–Lucas–Tomasi tracking algorithms	• training based on video clip and motion clip for classification	[33, 145]
Ivory-billed woodpecker	flying characteristics	• image processing• non-parametric motion filtering	• non-parametric motion filtering	• bird filter algorithm• similarity matching algorithm	• not required	[24]
Ivory-billed woodpecker	**flight characteristics** (speed etc.) + **silhouette** information	• binary segmentation (against sky)	• principal axes of silhouette• velocity and its derivatives	• spatio-temporal filters	• not required System selects the profile parameters based on anatomical knowledge	[146]

Table 5 Illustration of visual recognition approach for individual animal

Name of animals	Animal recognition based on primary biometric features	Computer vision and pattern recognition techniques			Image annotation	Ref.
		System modelling and feature learning principles	Image representation-based models	Matching and localisation techniques		
Elephants	**ear pattern** (shape of ear silhouette sections)	• edge tracing	• shape texture features of ear silhouette	• local edge refinement	• rough ear-line annotation	[38]
Grey seal (Halichoerus grypus)	**texture features** (dense skin texture body)	• gradient of texture features-based histograms	• binarised surface texture descriptor model	• covariance-based texture matching	• control points	[51]
Zebra	**body joint stripes** (binary pattern formed by stripe paths)	• median filter binarisation• run-length coding	• joint stripe (strip junction) strings	• dynamic programming• edit distance	• bounding box around body side	[39]
Masai giraffe	**head/body surface texture** (distinctive gradient orientation of head or body texture)	• computer vision	• SIFT descriptor approach• local feature	• k-D tree• similarity matching	• not required	[52]
Chimpanzee, gorilla	**facial features** (conglomerate of local and global face characteristics)	• computer vision model• appearance random faces	• appearance features and texture features (global and local features)	• random selection of facial features random faces	• not required	[40]
African penguin	**chest spot points** (configuration of discrete landmarks on chest feathers)	• polar spatial histograms	• shape contexts (feature descriptor)	• earth movers distance• phase curls	• not required	[50, 58]
Salamander	**body texture** (blob-like shape of markings over main body segment)	• coarse-to-fine decomposition using Gabor filters	• none, the method produces match decisions for input pairs	• scale-cascaded diffeomorphic alignment	• not required	[74]
Whale shark (Rhincodon typus)	**spotting points on body surface** (configuration of discriminatory landmarks on body surface)	• min–max• normalisation• descriptor learning model	• localisation of landmarks	• pattern-matching algorithm (based on Groth's algorithm)	• spot pattering-based verification	[37]
Cheetah (Acinonyx jubatus) tiger (Panthera tigris)	**body spot pattering structures and thin stripes** (configuration of discriminatory points on body)	• spline-model based texture feature	• spot pattering and landmarks neural network (NN) (backprojection method)	• similarity-based distance measure between spot pattering	• body landmarks annotated for training the systems	[51, 147, 148]
Leatherback turtle	**images feature** of their plastron (bright red regions located on the outer perimeter of the plastron)	• computer vision and pattern recognition	• image processing• NNs (multi-layer perceptron)	• colour-based thresholding	• not required	[149]
Ridleys turtle (Lepidochelys)	**shape, texture features** (length, breadth), colour extraction	• computer vision• pattern recognition	• MATLAB software tool• shape descriptor	• SIFT key point-based matching	• not required	[150]

The complexity of the system design in advance calls for inspired a new breed of scientists, researchers, biologically knowledgeable engineers and technical potential biologists. These must be cross-disciplinary engineers, scientists who have a devoted understanding of the target species and its habitat, as well as the technical tools that underpin practical engineering solutions. The future will show whether animal biometrics can live up to its promise of revolutionising the way we look at the phenotype.

Table 5 Continued

Name of animals	Animal recognition based on primary biometric features	Computer vision and pattern recognition techniques			Image annotation	Ref.
		System modelling and feature learning principles	Image representation-based models	Matching and localisation techniques		
Fish species	**colour, texture and shape features** (grey level image binarisation features)	• MATLAB software, computer vision model (active appearance)	• PCA	• Fisher classification model• Mahalanobis distance model• SPSS statistical model	• not required	[151], [176], [177], [178], [179], [182], [185]
	shape features, local features, texture, geometry features	• bag-of-words model computer vision model	• HOG descriptor• discrete cosine transformation	• RF classification• similarity matching	• not required	[152]
	texture features (head, caudal (tail)	• pattern recognition and computer vision models	• LBP texture feature technique	• SIFT descriptor-similarity matching	• not required	[153]
	texture features, shape features, (head, caudal (tail)	• non-rigid part model, feature descriptors	• SIFT descriptor• radial basis function	• hierarchical partial classifier, trajectory voting scheme	• not required	[154, 155]
Chimpanzee	**Facial images (identification of age group, and gender)**	• deep learning model• CNN	• appearance features	• log-Euclidean model for similarity matching	• Not required	[156]
Manta ray species	**body spot pattering** (localization and configuration of discriminatory landmarks body surface)	• Procrustes' alignment-based model	• discriminatory landmarks body surface	• Euclidean norm• L_2 distance measures• entropy calculation	• spot pattering as annotation	[157, 158]

Table 6 Behaviour analysis and recognition of species

Type of species	Types of behaviour/activity of species	Behaviour analysis and recognition of species			Ref.
		Modelling and machine learning strategies	Model representation for behavioural activities	Matching techniques	
Honey bees (for health monitoring)	**shimmering behaviour** (3D movements of hive)	• template matching	• 3D position estimation of individual bees	• triangulation of corresponding templates	[50]
mice (house)	**home cage activity** (major characteristics of particular activities in spatio-temporal domain)	• spatio-temporal volume analysis	• motion, position and velocity features	• SVM-based classifier	[37]
Birds	**nesting behaviour** (bird presence/absence at nest, egg count)	• classification based on local spatial frequency	• SIFT scales information	• Fisher linear discriminant• hidden Markov models	[48]
Wild type and Fmr1-KO (mice species)	**abnormal behaviour** (video tracking)	• passive RFID in ultra-high frequency band	• robust PCA	• K-NN classification	[159]
	home-cage activity (video)	• permutation entropy	• not required	• piezoelectric pressure-sensors	[160]
Mice	**mouse movement behaviour**	• HCI-based behaviour	• computer vision	• SVM classification	[161]
Blackcup (Sylvia atricapilla)	**migratory behaviour** (timing, duration and direction of migration)	• bias-adjustment algorithm that adjusts radar measures	• spatial displacement of radar targets	• correspondence matching between radar reflectivity data	[43, 162]
	flocking behaviour (trajectory in bird flock)	• tracking by positional beliefs	• particle cloud and co-ordinate system	• condensation algorithm	
Drosophila (fruit flies)	**standing, walking** off' (not in physical contact with egg-laying)	• CNNs (two-layer CNN)	• CNN feature-based representation model	• Euclidean distance-based similarity matching	[163]
	flocking behaviour	• ellipse model	• AdaBoost classifier	• not required	[164]
Laboratory animals'	**home cage, postures and activities behaviour**	• model-based articulated body parts, gradient vector flow	• Kalman filtering method, classification model	• Euclidean distance-based similarity matching	[165]

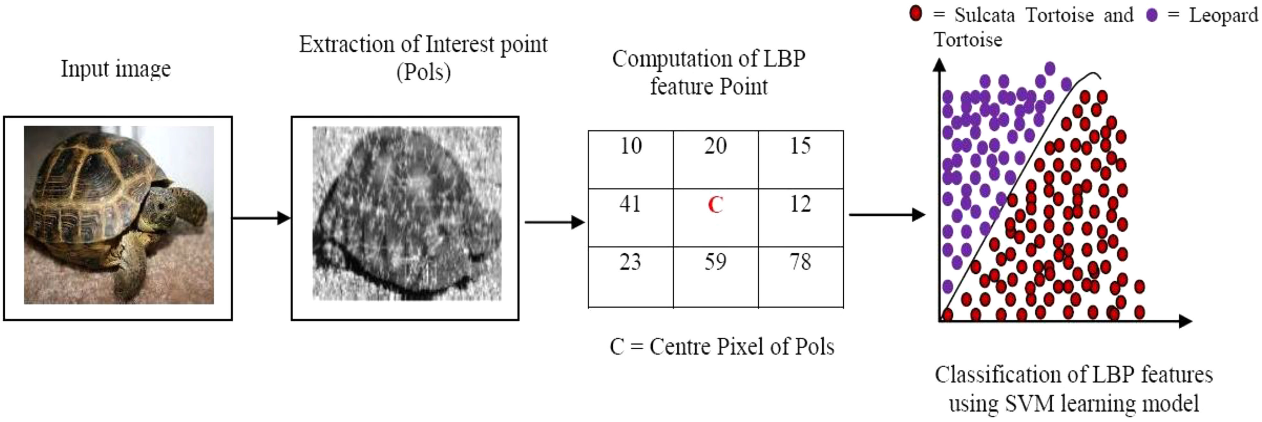


Fig. 9 *Illustrates the classification of LBP texture features of tortoise species using SVM technique*

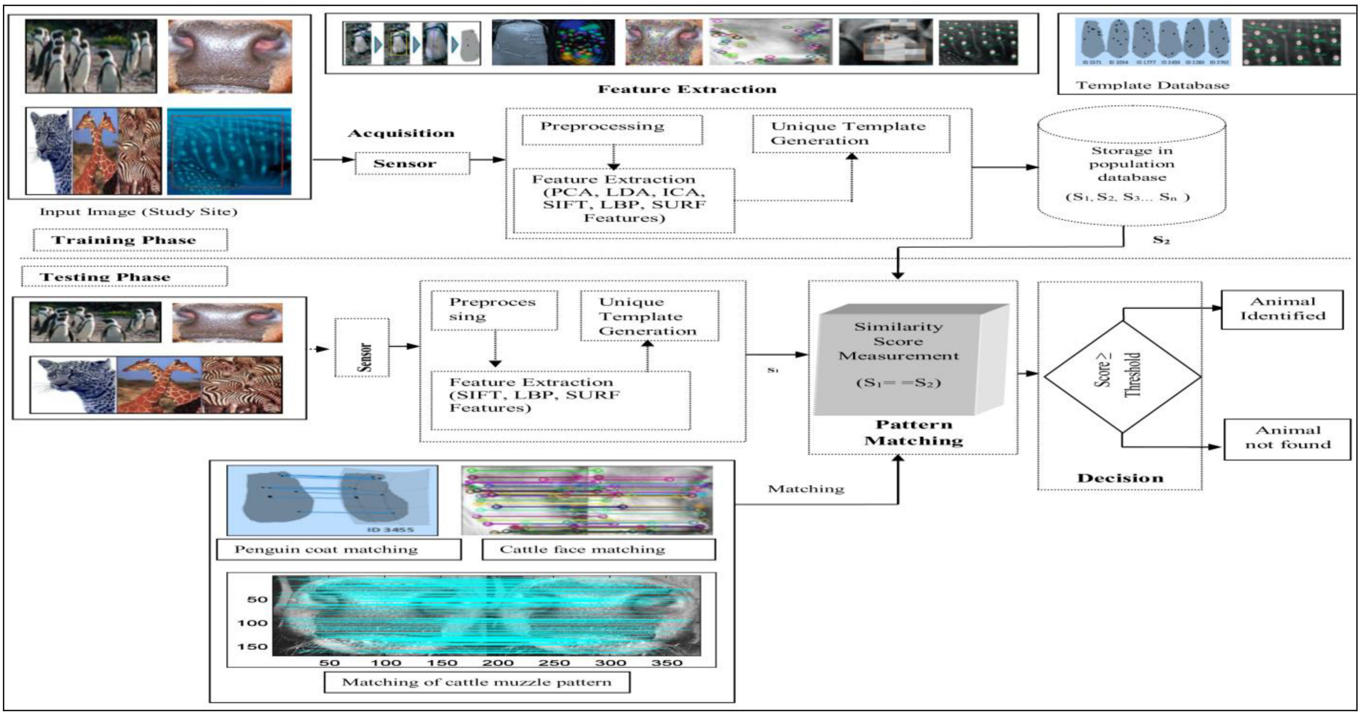


Fig. 10 *Illustrates the block diagram of proposed approach for visual animal biometric system for species or individual animal*

11 References

[1] Duyck, J., Finn, C., Hutcheon, A.*, et al.*: 'Sloop: a pattern retrieval engine for individual animal identification', *Pattern Recognit.*., 2015, **48**, (4), pp. 1059–1073

[2] Kühl, H.S., Burghardt, T.: 'Animal biometrics: quantifying and detecting phenotypic appearance', *Trends Ecol. Evol.*, 2013, **28**, (7), pp. 432–441

[3] Atanbori, J., Duan, W., Appiah, K.*, et al.*: 'A computer vision approach to classification of birds in flight from video sequences', 2015

[4] Scott, D.K.: 'Identification of individual Bewick's swans by bill patterns', in Stonehouse, B. (ED.): '*Animal marking: recognition marking of animals in research*' (MacMillan, UK, 1978), pp. 160–168

[5] Klingel, H.: 'Social organisation and behaviour of the Grevy's zebra', *Z. Tierpsychol.*, 1974, **36**, pp. 36–70

[6] Mizroch, S.A., Harkness, S.A.D.: 'A test of computer-assisted matching using the North Pacific humpback whale, Megapteranovaeangliae, tail flukes photograph collection', *Mar. Fish. Rev.*, 2003, **65**, pp. 25–37

[7] Bonnell, T.R., Henzi, S.P., Barrett, L.: 'Sparse movement data can reveal social influences on individual travel decisions', arXiv preprint arXiv: 1511.01536, 2015

[8] Forsyth, D.: 'Building models of animals from video', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2006, **28**, (8), pp. 1319–1334

[9] Felzenszwalb, P.F., Girshick, R.B., McAllester, D.*, et al.*: 'Object detection with discriminatively trained part based models', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2010, **32**, pp. 1627–1645

[10] Pons-Moll, G., Baak, A., Gall, J.*, et al.*: 'Outdoor human motion capture using inverse kinematics and von Mises-Fisher sampling'. Int. Conf. on Computer Vision, Barcelona, November 2011, pp. 1243–1250

[11] Shotton, J., Sharp, T., Kipman, A.*, et al.*: 'Real-time human pose recognition in parts from single depth images'. IEEE Computer Vision and Pattern Recognition (CVPR), Providence, RI, June 2011, pp. 1297–1304

[12] Kumar, R.: 'Trainable convolution filters and their application to face recognition', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2012, **34**, pp. 1423–1436

[13] Wright, J.A., Barker, R.J., Schofield, M.R.*, et al.*: 'Incorporating Genotype Uncertainty into Mark-Recapture-Type Models For Estimating Abundance Using DNA Samples', *Biometrics*, 2009, **65**, (3), pp. 833–840

[14] Poppe, R.: 'A survey on vision-based human action recognition', *Image Vis. Comput.*, 2010, **28**, (6), pp. 976–990

[15] Wang, L., Suter, D.: 'Learning and matching of dynamic shape manifolds for human action recognition', *IEEE Trans. Image Process.*, 2007, **16**, pp. 1646–1661

[16] Pfister, T.: 'Differentiating spontaneous from posed facial expressions within a generic facial expression recognition framework'. IEEE Int. Conf. Computer Vision Workshops (ICCV Workshops), Barcelona, January 2011, pp. 868–875

[17] Gomez-Marin, A., Paton, J.J., Kampff, A.R.*, et al.*: 'Big behavioral data: psychology, ethology and the foundations of neuroscience', *Nat. Neurosci.*, 2014, **17**, (11), pp. 1455–1462

[18] Azhar, M.A.H.B., Hoque, S., Deravi, F.: 'Automatic identification of wildlife using local binary patterns'. IET Conf. on Image Processing (IPR), London, July 2012, pp. 1–6

[19] Speed, C.W., Meekan, M.G., Bradshaw, C.J.: 'Spot the match: wildlife photo-identification using information theory', *Frontiers in zoology*, 2007, **4**, (2), pp. 1–11

[20] Ahmadian, S.: 'Heartbeat of a nest: using imagers as biological sensors', *ACM Trans. Sensor Netw. (TOSN)*, 2010, **6**, (3), p. 19

[21] Estellés-Arolas, E., Navarro-Giner, R., González-Ladrón-de-Guevara, F.: 'Crowdsourcing Fundamentals: Definition and Typology', in Garrigos-Simon, F.J., Gil-Pechuán, I., Estelles-Miguel, S. (EDS.): '*Advances in Crowdsourcing*' (Springer International Publishing, 2015), pp. 33–48

[22] Dietterich, T.G.: 'Machine learning in ecosystem informatics and sustainability'. 21st Int. Joint Conf. on Artificial Intelligence, Pasadena, California, July 2009, pp. 8–13

[23] Coates, A., Karpathy, A., Ng, A.Y.: 'Emergence of object-selective features in unsupervised feature learning', *Adv. Neural Inf. Process. Syst.*, 2012, **25**, pp. 2690–2698

[24] Song, D., Qin, N., Xu, Y., *et al.*: 'System and algorithms for an autonomous observatory assisting the search for the ivory-billed woodpecker'. IEEE Int. Conf. on Automation Science and Engineering, Arlington, VA, August 2008, pp. 200–205

[25] Croll, D.A., Dewar, H., Dulvy, N.K., *et al.*: 'Vulnerabilities and fisheries impacts: the uncertain future of manta and devil rays', *Aquatic Conserv., Mar. Freshwater Ecosyst.*, 2015, **26**, 3, pp. 562–575

[26] Marshall, A.D., Pierce, S.J.: 'the use and abuse of photographic identification in sharks and rays', *J. Fish Biol.*, 2012, **80**, pp. 1361–1379

[27] Brooks, K., Rowat, D., Pierce, S.J., *et al.*: 'Seeing spots: photo-identification as a regional tool for whale shark identification', *West. Indian Ocean J. Mar. Sci.*, 2010, **9**, (2), pp. 185–194

[28] Arzoumanian, Z., Holmberg, J., Norman, B.: 'An astronomical pattern-matching algorithm for computer-aided identification of whale sharks Rhincodontypu', *J. Appl. Ecol.*, 2005, **42**, (6), pp. 999–1011

[29] www.snapshotserengeti.org/ accessed on 10 December, 2015

[30] Jain, A., Maltoni, D., Maio, D., *et al.*: '*Biometric systems: technology, design and performance evaluation*' (Springer, 2005)

[31] Jain, A.K., Flynn, P., Ross, A.A.: '*Handbook of biometrics*' (Springer Science & Business Media, New York, 2007)

[32] Mikolajczyk, K., Schmid, C.: 'A performance evaluation of local descriptors', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2004, **2**, pp. 257–263

[33] Hannuna, S.L., Campbell, N.W., Gibson, D.P.: 'Identifying quadruped gait in wildlife video'. IEEE Int. Conf. Image Processing (ICIP), Genova, Italy, September 2005, vol. **1**, pp. 710–713

[34] Reilly, V., Idrees, H., Shah, M.: 'Detection and tracking of large number of targets in wide area surveillance'. 11th European Conf. on Computer Vision, Heraklion, Crete, Greece, September 5–11, 2010, pp. 186–199

[35] Wang, Z., Fan, B.: 'Local intensity order pattern for feature description'. IEEE Int. Conf. on Computer Vision, Barcelona, January 2011, pp. 603–610

[36] Jain, A.K.: 'Biometric recognition: how do I know who you are?'. Signal Processing and Communications Applications, April 2004, pp. 3–5, doi: 10.1109/SIU.2004.1338241

[37] Holmberg, J., Norman, B., Arzoumanian, Z., *et al.*: 'Estimating population size, structure, and residency time for whale sharks Rhincodontypus through collaborative photo-identification', *Endangered Species Res.*, 2009, **7**, (1) pp. 39–53

[38] Ardovini, A., Cinque, L., Sangineto, E.: 'Identifying elephant photos by multi-curve matching', *Pattern Recognit.'*, 2008, **41**, pp. 1867–1877

[39] Lahiri, M., Tantipathananandh, C., Warungu, R., *et al.*: 'Biometric animal databases from field photographs: identification of individual zebra in the wild'. First ACM Int. Conf. on Multimedia Retrieval, Trento, Italy, April 2011, pp. 6:1s–66:8

[40] Loos, A., Pfitzer, M.: 'Towards automated visual identification of primates using face recognition'. 19th Int. Conf. on Systems, Signals and Image Processing (IWSSIP), Vienna, April 2012, pp. 425–428

[41] Domeier, M.L., Nasby-Lucas, N.: 'Annual re-sightings of photographically identified white sharks (Carcharodoncarcharias) at an eastern Pacific aggregation site (Guadalupe Island, Mexico)', *Mar. Biol.*, 2007, **150**, pp. 977–984

[42] Ernst, A., Ku blbeck, C.: 'Fast face detection and species classification of African great apes'. Eigth IEEE Int. Conf. on Advanced Video and Signal-Based Surveillance, Klagenfurt, September 2011, pp. 279–284

[43] Zhang, W., Sun, J., Tang, X.: 'From tiger to panda: animal head detection', *IEEE Trans. Image Process.*, 2011, **20**, pp. 1696–1708

[44] Finn, C., Duyck, J., Hutcheon, A., *et al.*: 'Relevance feedback in biometric retrieval of animal photographs', in Martinez-Trinidad, J.F., Carrasco-Ochoa, J.A., Olvera López, J.A. (EDS.): '*Pattern recognition*' (Springer International Publishing, 2014), pp. 281–290

[45] Kumar, S., Singh, S.K.: 'Biometric recognition for pet animal', *J. Softw. Eng. Appl.*, 2014, **7**, (5), pp. 470–482

[46] Volk, T., Gorbey, S., Bhattacharyya, M., *et al.*: 'RFID technology for continuous monitoring of physiological signals in small animals', *IEEE Trans. Biomed. Eng.*, 2015, **62**, (2), pp. 618–626

[47] Tweed, D., Calway, A.: 'Tracking many objects using subordinated condensation'. Proc. of the British Machine Vision Conf., October 2002, pp. 283–292

[48] Baranov, A.S., Graml, R., Pirchner, F., *et al.*: 'Breed differences and intra-breed genetic variability of dermatoglyphic pattern of cattle', *J. Anim. Breed. Genet.*, 1993, **11**, (1-6), pp. 385–392

[49] Noviyanto, A., Arymurthy, A.M.: 'Beef cattle identification based on muzzle pattern using a matching refinement technique in the SIFT method', *Comput. Electron. Agric.*, 2013, **99**, pp. 77–84

[50] Burghardt, T., Campbell, N.: 'Generic phase curl localisation for an individual identification of Turing-patterned animals'. Visual Observation and Analysis of Animal and Insect Behavior, 2010, pp. 17–21

[51] Hiby, L., Lovell, P., Patil, N., *et al.*: 'A tiger cannot change its stripes: using a three-dimensional model to match images of living tigers and tiger skins', *Biol. Lett.*, 2009, **5**, pp. 383–386

[52] Bolger, D.T., Morrison, T.A., Vance, B., *et al.*: 'A computer-assisted system for photographic mark–recapture analyses', *Methods Ecol. Evol.*, 2012, **3**, pp. 813–822

[53] Ahmed, S., Gaber, T., Tharwat, A., *et al.*: 'Muzzle-based cattle identification using speed up robust feature approach'. IEEE Int. Conf. on Intelligent Networking and Collaborative Systems (INCOS), Taipei, 2015, pp. 99–104

[54] Petherick, J.C.: 'Animal welfare issues associated with extensive livestock production: the northern Australian beef cattle industry', *Appl. Anim. Behav. Sci.*, 2005, **9**, (3), pp. 211–234

[55] Mahmoud, H.A., Hadad, H.M.R.E.: 'Automatic cattle muzzle print classification system using multiclass support vector machine', *Int. J. Image Mining*, 2015, **1**, pp. 126–140

[56] Papadakis, V.M.: 'A computer-vision system and methodology for the analysis of fish behaviour', *Aquac. Eng.*, 2012, **46**, pp. 53–59

[57] Larios, N., Deng, H., Zhang, W., *et al.*: 'Automated insect identification through concatenated histograms of local appearance features', *Mach. Vis. Appl.*, 2008, **19**, pp. 105–123

[58] Sherley, R.B., Burghardt, T., Barham, P.J., *et al.*: 'Spotting the difference: towards fully automated population monitoring of African penguins Spheniscusdemersus', *Endangered Species Res.*, 2010, **11**, pp. 101–111

[59] Jhuang, H., Garrote, E., Yu, X., *et al.*: 'Automated home-cage behavioural phenotyping of mice', *Nat. Commun.*, 2010, **1**, p. 68

[60] Viola, P., Jones, M.J., Snow, D.: 'Detecting pedestrians using patterns of motion and appearance'. IEEE Int. Conf. on Computer Vision, Nice, France, October 2003, pp. 734–741

[61] Dell, A.I., Bender, J.A., Branson, K., *et al.*: 'Automated image-based tracking and its application in ecology', *Trends Ecol. Evol.*, 2014, **29**, (7), pp. 417–428

[62] Petrovska-Delacretaz, D., Edwards, A., Chiasson, J., *et al.*: 'A reference system for animal biometrics: Application to the northern leopard frog'. First Int. Conf. on Advanced Technologies for Signal and Image Processing (ATSIP), Sousse, March 2014, pp. 295–300

[63] Viola, P., Jones, M.: 'Rapid object detection using a boosted cascade of simple features'. IEEE Int. Conf. on Computer Vision and Pattern Recognition (CVPR), Kauai, HI, USA, December 2001, vol. **1**, pp. 511–518

[64] Butynski, T.M.: 'Comparative ecology of blue monkeys (Cercopithecusmitis) in high-and low-density subpopulations', *Ecol. Monogr.*, 1990, **60**, 1, pp. 1–26

[65] Morand Ferron, J., Cole, E.F., Quinn, J.L.: 'Studying the evolutionary ecology of cognition in the wild: a review of practical and conceptual challenges', *Biol. Rev.*, 2015, **91**, (2), pp. 367–389

[66] Royle, J.A., Dorazio, R.M.: '*Hierarchical modeling and inference in ecology: the analysis of data from populations, meta populations and communities*' (Academic Press, 2008)

[67] Chen, S., Ilany, A., White, B.J., *et al.*: 'Spatial-temporal dynamics of high-resolution animal networks: what can we learn from domestic animals?', *PloS one*, 2015, **10**, (6), p. e0129253

[68] De Groeve, J., Van de Weghe, N., Ranc, N., *et al.*: 'Extracting spatiotemporal patterns in animal trajectories: an ecological application of sequence analysis methods', *Methods Ecol. Evol.*, 2015, **7**, (3), pp. 369–379

[69] Óscar, M., Pep-Luis, M., Sergio, M., *et al.*: 'APHIS: a new software for photo-matching in ecological studies', *Ecol. Inf.*, 2015, **27**, pp. 64–70

[70] Ravela, S., Duyck, J., Finn, C.: 'Vision-based biometrics for conservation'. MCPR, 2013, pp. 10–19

[71] Wu, S., Moore, B.E., Shah, M.: 'Chaotic invariants of Lagrangian particle trajectories for anomaly detection in crowded scenes'. IEEE Conf. on Computer Vision and Pattern Recognition, San Francisco, CA, June 2010, pp. 2054–2060

[72] http://www.whaleshark.org.au/photo-id-library/ accessed on 20 December 2015

[73] Gaston, K.J., O'Neill, M.A.: 'Automated species identification: why not?', *Philos. Trans. R. Soc. Lond. B*, 2004, **359**, pp. 655–667

[74] Burghardt, T., Calic, J.: 'Real-time face detection and tracking of animals'. Eigth IEEE Seminar on Neural Network Applications in Electrical Engineering, Belgrade, Serbia & Montenegro, September 2006, pp. 27–32

[75] Baig, A., Bouridane, A., Kurugollu, F., *et al.*: 'Cascaded multimodal biometric recognition framework', *IET Biometrics*, 2014, **3**, (1), pp. 16–28

[76] Hassaballah, M., Aly, S.: 'Face recognition: challenges, achievements and future directions', *IET Comput. Vis.*, 2015, **9**, (4), pp. 614–626

[77] Johnston, A.M., Edwards, D.S.: 'Welfare implications of identification of cattle by ear tags', *Veterinary Rec.*, 1996, **138**, (25), pp. 612–614

[78] Pennington, J.A.: 'Tattooing of Cattle and Goats, University of Arkansas', United States Department of Agriculture, and County Governments Cooperating, 2012

[79] Awad, A.I., Zawbaa, H.M., Mahmoud, H.A., *et al.*: 'A robust cattle identification scheme using muzzle print images'. Federated Conf. on IEEE Computer Science and Information Systems (FedCSIS), Kraków, Poland, September 2013, pp. 529–534

[80] Wardrope, D.D.: 'Problems [suppurating wounds] with the use of ear tags in cattle [Correspondence]', *Veterinary Rec.*, 1995, **137**, (26), p. 675

[81] Kumar, S., Tiwari, S., Singh, S.K.: 'Face recognition of cattle: can it be done?', *Proc. Nat. Acad. Sci., India A, Phys. Sci.*, 2016, **86**, (2), pp. 137–148, pp. 1–12, doi: 10.1007/s40010-016-0264-2

[82] Minagawa, H., Fujimura, T., Ichiyanagi, M., *et al.*: 'Identification of beef cattle by analysing images of their muzzle patterns lifted on paper', *Publ. Jpn. Soc. Agric. Inform.*, 2002, **8**, pp. 596–600

[83] Noviyanto, A., Arymurthy, A.M.: 'Automatic cattle identification based on muzzle photo using speed-up robust features approach'. Proc. of 3rd European Conf. of Computer Science (ECCS), 2012, vol. **110**, p. 114

[84] Mishra, S., Tomer, O.S., Kalm, E.: 'Muzzle dermatoglyphics: a new method to s: a new method to identify bovines', Asian Livestock, 1995, pp. 91–96

[85] Kumar, S., Singh, S.K.: 'Feature selection and recognition of muzzle pattern of cattle by using hybrid chaos BFO and PSO algorithms', in Azar, A.T., Vaidyanathan, S. (EDS.): *'Advances in chaos theory and intelligent control', Studies in Fuzziness and Soft Computing* (Springer-Verlag, Germany, 2015)

[86] Kumar, S., Singh, S.K., Dutta, T., *et al.*: 'Poster: a real-time cattle recognition system using wireless multimedia networks'. Proc. of the 14th Annual Int. Conf. on Mobile Systems, Applications, and Services Companion, 2016, pp. 48–48

[87] Kumar, S., Singh, S.K.: 'Feature selection and recognition of face by using hybrid chaotic PSO-BFO and appearance-based recognition algorithms', *Int. J. Nat. Comput. Res. (IJNCR)*, 2015, **5**, (3), pp. 26–53

[88] Kumar, S., Singh, S.K.: 'Automatic identification of cattle using muzzle point pattern: a hybrid feature extraction and classification paradigm', Multimedia Tools and Applications, Springer, 2016, doi: 10.1007/s11042-016-4181-9

[89] Kumar, S., Singh, S.K., Shrikant, R.S., *et al.*: 'Real-time cattle recognition using animal biometrics', *J. Real-Time Image Process.*, 2016, pp. 1–22, doi: 10.1007/s11554-016-0645-4

[90] Kumar, S., Singh, S.K.: 'Hybrid BFO and PSO swarm intelligence approach for biometric feature optimization', *Int. J. Swarm Intell. Res. (IJSIR)*, 2016, **7**, (2), pp. 36–62

[91] Kumar, S., Singh, S.K., Datta, T., *et al.*: 'A fast cattle recognition system using smart devices'. Proc. of the 2016 ACM on Multimedia Conf. 2016, 2016, pp. 742–743

[92] Barry, B., Gonzales-Barron, U.A., McDonnell, K., *et al.*: 'Using muzzle pattern recognition as a biometric approach for cattle identification', *Am. Soc. Agric. Biol. Eng.*, 2007, **50**, (3), pp. 1073–1080

[93] Kim, H.T., Ikeda, Y., Choi, H.L.: 'The identification of Japanese black cattle by their faces', *Training*, 2005, **1, p**. e11e12

[94] Cheng, C., Li, J.: 'Cattle face recognition using local binary pattern descriptor'. IEEE, Annual Summit and Conf. on Signal and Information Processing Association (APSIPA), Asia-Pacific, Kaohsiung, November 2013, pp. 1–4, doi: 10.1109/APSIPA.2013.6694369

[95] Thaxter, C.B., Ross Smith, V.H., Clark, J.A., *et al.*: 'Contrasting effects of GPS device and harness attachment on adult survival of Lesser Black-backed Gulls Larusfuscus and Great SkuasStercorariusskua'. IBIS, 2016

[96] Ahumada, J.A., Silva, C.E., Gajapersad, K., *et al.*: 'Community structure and diversity of tropical forest mammals: data from a global camera trap network', *Philos. Trans. R. Soc. Lond. B*, 2011, **366**, pp. 2703–2711

[97] Buckland, S.T., Burt, M.L., Rexstad, E.A., *et al.*: 'Aerial surveys of seabirds: the advent of digital methods', *J. Appl. Ecol.*, 2012, **49**, pp. 960–967

[98] Watts, A.C., Perry, J.H., Smith, S.E., *et al.*: 'Small unmanned aircraft systems for low altitude aerial surveys', *J. Wildl. Manage.*, 2010, **74**, (7), pp. 1614–1619

[99] Damm, P.E., Grand, J.B., Barnett, S.W.: 'Variation in detection among passive infrared triggered-cameras used in wildlife research', *Proc. Annu. Conf. Southeast Assoc. Fish Wildl. Agencies*, 2010, **64**, pp. 125–130

[100] Saraux, C., Le Bohec, C., Durant, J.M., *et al.*: 'Reliability of flipper-banded penguins as indicators of climate change', *Nature*, 2011, **469**, pp. 203–206

[101] Tharwat, A., Gaber, T., Hassanien, A.E.: 'Cattle identification based on muzzle images using Gabor features and SVM classifier', in Hassanien, A.E., Tolba, M.F., Taher, A.A. (EDS.): '*Advanced machine learning technologies and applications*' AMLTA (Springer, Cham 2014), **488**, pp. 236–247, Communications in Computer and Information Science

[102] Petersen, W.: 'The identification of the bovine by means of nose-prints', *J. Dairy Sci.*, 1922, **5**, (1), pp. 249–258

[103] Hochachka, W.M., Fink, D., Hutchinson, R.A., *et al.*: 'Data-intensive science applied to broad scale citizen science', *Trends Ecol. Evol.*, 2012, **27**, pp. 130–137

[104] Kranner, I., Bischof, H.: 'Stereoscopic motion analysis in densely packed clusters: 3D analysis of the shimmering behaviour in giant honey bees', *Front. Zool.*, 2011, **8**, (3), p. 3, doi: 10.1186/1742-9994-8-3

[105] Yang, J.: 'The thin plate spline robust point matching (TPS-RPM) algorithm: a revisit', *Pattern Recognit. Lett.*, 2011, **32**, pp. 910–918

[106] Clutton-Brock, T.H., Sheldon, B.C.: 'Individuals and populations: the role of long-term, individual-based studies of animals in ecology and evolutionary biology', *Trends Ecol. Evol.*, 2010, **25**, pp. 562–573

[107] Kappeler, P., Watts, D.: '*Long-term field studies of primates*' (Springer, 2011)

[108] Magurran, A.E., Baillie, S.R., Buckland, S.T., *et al.*: 'Long-term datasets in biodiversity research and monitoring: assessing change in ecological communities through time', *Trends Ecol. Evol.*, 2010, **25**, pp. 574–582

[109] Houle, D., Govindaraju, D.R., Omholt, S.: 'Phenomics: the next challenge', *Nat. Rev. Genet.*, 2010, **11**, pp. 855–866

[110] Sandbrook, C.: 'The social implications of using drones for biodiversity conservation', *Ambio*, 2015, **44**, (4), pp. 636–647

[111] http://sourceforge.net/projects/cheetahdatabase accessed on 27 December 2015, time 11: 45 am

[112] Hsieh, H.M., Huang, L.H., Tsai, L.C., *et al.*: 'Species identification of rhinoceros horns using the cytochrome b gene', *Forensic Sci. Int.*, 2003, **136**, (1), pp. 1–11

[113] Hochachka, W.M., Fink, D., Hutchinson, R.A., *et al.*: 'Data-intensive science applied to broad-scale citizen science', *Trends Ecol. Evol.*, 2015, **27**, 2, pp. 130–137

[114] http://www.ecoceanusa.org/shepherd accessed on 30 December 2015, time 10: 42 am

[115] Walters, C.L., Freeman, R., Collen, A., *et al.*: 'A continental-scale tool for acoustic identification of European bats', *J. Appl. Ecol.*, 2012, **49**, pp. 1064–1074

[116] Town, C., Marshall, A., Sethasathien, N.: 'Manta Matcher: automated photographic identification of manta rays using keypoint features', *Ecol. Evol.*, 2013, **3**, (7), pp. 1902–1914

[117] Heblich, S., Lameli, A., Riener, G.: 'Correction: the effect of perceived regional accents on individual economic behavior: a lab experiment on linguistic performance, cognitive ratings and economic decisions', *PloS One*, 2015, **10**, p. 5

[118] http://sharkidnetwork.com/about/ accessed on 27 December 2015, time 11: 45 am

[119] Jones, K.E., Bielby, J., Cardillo, M., *et al.*: 'PanTHERIA: a species-level database of life history, ecology, and geography of extant and recently extinct mammals: Ecological Archives E090-184', *Ecology*, 2009, **90**, (9), pp. 2648–2648

[120] Van Parijs, S.M., Clark, C.W., Sousa-Lima, R.S., *et al.*: 'Management and research applications of real-time and archival passive acoustic sensors over varying temporal and spatial scales', *Mar. Ecol. Prog. Ser.*, 2009, **395**, pp. 21–36

[121] Crall, J.D., Gravish, N., Mountcastle, A.M., *et al.*: 'BEE tag: a low-cost, image-based tracking system for the study of animal behavior and locomotion', *PloS One*, 2015, **10**, (9), p. e0136487

[122] http://www.csiro.au/Organisation-Structure/Divisions/Ecosystem-Sciences/ANWC-Sound-Archive, accessed on 30 December 2015, time 10: 42 am

[123] http://groups.inf.ed.ac.uk/f4k/GROUNDTRUTH/BEHAVIOR/, accessed on 07 September 2016, 20. 15 pm

[124] Oshizaki, J., Pollock, K.H., Brownie, C., *et al.*: 'Modeling misidentification errors in capture-recapture studies using photographic identification of evolving marks', *Ecology*, 2009, **90**, pp. 3–9

[125] Morrison, T.A., Yoshizaki, J., Nichols, J.D., *et al.*: 'Estimating survival in photographic capture–recapture studies: overcoming misidentification error. Methods', *Ecol. Evol.*, 2011, **2**, pp. 454–463

[126] Constantine, R., Jackson, J.A., Steel, D., *et al.*: 'Abundance of humpback whales in oceania using photo-identification and microsatellite genotyping', *Mar. Ecol. Prog. Ser.*, 2012, **453**, pp. 249–261

[127] Guo, S., Qiang, M., Luan, X., *et al.*: 'The application of the Internet of Things to animal ecology', *Integr. Zool.*, 2015, **10**, (6), pp. 572–578

[128] Zhang, W.: 'Cat head detection: how to effectively exploit shape and texture features', *Lect. Notes Comput. Sci.*, 2008, **5305**, pp. 802–816

[129] Sagonas, C., Panagakis, Y., Zafeiriou, S., *et al.*: 'Robust statistical frontalization of human and animal faces', *Int. J. Comput. Vis.*, 2016, pp. 1–22, doi: 10.1007/s11263-016-0920-7

[130] Chen, Y.-C., Hidayati, S.C., Cheng, W.-H., *et al.*: 'Locality constrained sparse representation for cat recognition'. 22nd Int. Conf., MMM 2016, Miami, FL, USA, January 2016, pp. 140–151

[131] Jarraya, I., Ouarda, W., Alimi, A.M.: 'A preliminary investigation on horses recognition using facial texture features'. IEEE Int. Conf. on Systems, Man, and Cybernetics (SMC), Kowloon, October 2015, pp. 2803–2808

[132] Galimberti, F., Sanvito, S.: 'Environmental research at Sea Lion Island'. Falkland Islands Field work report 2015/2016, 2016

[133] Liu, J., Kanazawa, A., Jacobs, D., *et al.*: 'Dog breed classification using part localization'. 12th European Conf. on Computer Vision, Florence, Italy, 7–13 October 2012, pp. 172–185

[134] Chen, J., Wen, Q., Qu, W., *et al.*: 'Panda facial region detection based on topology modelling'. 5th Int. Congress on Image and Signal Processing (CISP), Chongqing, Sichuan, China, October 2012, pp. 911–915

[135] Qi, Y., Cinar, G.T., Souza, V.M.A., *et al.*: 'Effective insect recognition using a stacked autoencoder with maximum correntropy criterion'. IEEE Int. Joint Conf. on Neural Networks (IJCNN), Killarney, July 2015, pp. 1–7

[136] Carlos, J., Reyesvera, U., Possani-Espinosa, A.: 'Scorpions: Classification of poisonous species using shape features'. Int. Conf. on Electronics Communications and Computers (CONIELECOMP), Cholula, February 2016, pp. 125–129

[137] Silva, D.F., Batista, G.E.D.A.P.A.: 'Signal classification by similarity and feature extraction with application in automatic insect identification'. Congresso da Sociedade Brasileira de Computação, XXXV; Concurso de Teses e Dissertações, XXVIII, Universidade Federal de Pernambuco-UFPE, 2015

[138] Lu, A., Hou, X., Liu, C.L., *et al.*: 'Insect species recognition using discriminative local soft coding'. 21st Int. Conf. on Pattern Recognition (ICPR), Tsukuba, November 2012, pp. 1221–1224

[139] Van Horn, G., Branson, S., Farrell, R., *et al.*: 'Building a bird recognition app and large scale dataset with citizen scientists: The fine print in fine-grained dataset collection'. IEEE Conf. on Computer Vision and Pattern Recognition, Boston, MA, June 2015, pp. 595–604

[140] Takeki, A., Trinh, T.T., Yoshihashi, R., *et al.*: 'Detection of small birds in large images by combining a deep detector with semantic segmentation'. IEEE Int. Conf. Image Processing, Phoenix, AZ, USA, September 2016, pp. 3977–3981

[141] Li, W., Song, D.: 'Automatic bird species filtering using a multimodal approach', *IEEE Trans. Autom. Sci. Eng.*, 2015, **12**, pp. 553–564

[142] Kiapour, M.H., Jagadeesh, W., Di, V., *et al.*: 'Mine the fine: Fine-grained fragment discovery'. IEEE Int. Conf. on Image Processing (ICIP), Quebec City, QC, September 2015, pp. 3555–3559

[143] Atanbori, J., Duan, W., Murray, J., *et al.*: 'Automatic classification of flying bird species using computer vision techniques', *Pattern Recognit. Lett.*, 2016, **81**, (1), pp. 53–62

[144] Wilson, D.J., Lyver, P.O.B., Greene, T.C., *et al.*: 'South Polar Skua breeding populations in the Ross Sea assessed from demonstrated relationship with Adélie Penguin numbers', *Polar Biol.*, pp. 1–16, doi:10.1007/s00300-016-1980-4

[145] Krüger, B., Yasin, H., Zsoldos, R., *et al.*: 'Retrieval, recognition and reconstruction of quadruped motions'. Int. Conf. on Computer Graphics Theory and Applications (GRAPP), Lisbon, Portugal, January 2014, pp. 1–8

[146] Song, D., Qin, N., Xu, Y., *et al.*: 'System and algorithms for an autonomous observatory assisting the search for the Ivory-Billed Woodpecker'. IEEE Int. Conf. on Automation Science and Engineering, Arlington, VA, 2008, pp. 200–205

[147] Kelly, M.J.: 'Computer-aided photograph matching in studies using individual identification: an example from Serengeti cheetahs', *J. Mammal.*, 2001, **82**, pp. 440–449

[148] Chelysheva, E.: 'A new approach to cheetah identification', CAT NEWS, IUCN/CSG 41, 2004, pp. 27–29

[149] Beugeling, T., Branzan-Albu, A.: 'Computer vision-based identification of individual turtles using characteristic patterns of their plastrons'. Canadian Conf. on Computer and Robot Vision (CRV), Montreal, QC, 2014, pp. 203–210

[150] Baboo, S.S., Vigneswari, A.R.J.: 'Identification of olive Ridley turtle using feature extraction'. Int. Conf. on Intelligent Computing Applications (ICICA), Coimbatore, October 2014, pp. 69–72
[151] Li, L., Hong, J.: 'Identification of fish species based on image processing and statistical analysis research'. IEEE Int. Conf. on Mechatronics and Automation, Tianjin, August 2014, pp. 1155–1160
[152] Saitoh, T., Shibata, T., Miyazono, T.: 'Image-based fish recognition'. Seventh Int. Conf. of Soft Computing and Pattern Recognition (SoCPaR), Fukuoka, Japan, August 2015, pp. 260–263
[153] Chuang, M.C., Hwang, J.N., Williams, K.: 'Supervised and unsupervised feature extraction methods for underwater fish species recognition'. Computer Vision for Analysis of Underwater Imagery (CVAUI), 2014 ICPR Workshop on, Stockholm, August 2014, pp. 33–40
[154] Chuang, M.C., Hwang, J.N., Williams, K.: 'A feature learning and object recognition framework for underwater fish images', *IEEE Trans. Image Process.*, 2016, **25**, pp. 1862–1872
[155] Ashour, H., Sasi, S.: 'Recognition of stonefish from underwater video'. Int. Conf. on Advances in Computing Communications and Informatics (ICACCI), Kochi, August 2015, pp. 1031–1036
[156] Freytag, A., Rodner, E., Simon, M., *et al.*: 'Chimpanzee faces in the wild: log-Euclidean CNNs for predicting identities and attributes of primates'. 38th German Conf., GCPR, Hannover, Germany, September 2016, pp. 12–15
[157] Marshall, A.D., Pierce, S.J., Bennett, M.B.: 'Morphological measurements of manta rays (Manta birostris) with a description of a foetus from the east coast of Southern Africa', *Zootaxa*, 2008, **1717**, pp. 24–30
[158] Martin-Smith, K.M.: 'Photo-identification of individual weedy sea dragons Phyllopteryxtaeniolatus and its application in estimating population dynamics', *J. Fish Biol.*, 2011, **78**, pp. 1757–1768
[159] Macrì, S., Mainetti, L., Patrono, L., *et al.*: 'A tracking system for laboratory mice to support medical researchers in behavioral analysis'. 37th Annual IEEE Int. Conf. on Engineering in Medicine and Biology Society (EMBC), Milan, August 2015, pp. 4946–4949
[160] Carreno, M.I., López de Ipiña, K., Beitia, B.: 'First approach to the analysis of spontaneous activity of mice based on Permutation Entropy'. Fourth IEEE Int. Work Conf. on Bioinspired Intelligence (IWOBI), San Sebastian, June 2015, pp. 197–204
[161] Hamid, N.A., Safei, S., Satar, S.D.M., *et al.*: 'Mouse movement behavioral biometric systems'. Int. Conf. on User Science and Engineering (i-USEr), Shah Alam, Selangor, December 2011, pp. 206–211
[162] Sieges, M.L., Smolinsky, J.A., Baldwin, M.J., *et al.*: 'Assessment of bird response to the migratory bird habitat initiative using weather-surveillance radar', *Southeast. Nat.*, 2014, **13**, (1), pp. G36–G65
[163] Stern, U., He, R., Yang, C.H.: 'Analyzing animal behavior via classifying each video frame using convolutional neural networks', Scientific reports, 5, Article number: 14351 2015, doi: 10.1038/srep14351
[164] Fan, J., Jiang, N., Wu, Y.: 'Automatic video-based analysis of animal behaviors'. IEEE Int. Conf. Image Processing, Hong Kong, September 2010, pp. 1513–1516
[165] Mayya, M., Doignon, C.: 'Visual tracking of small animals based on real-time Level Set Method with fast infra-red thermographic imaging'. IEEE Int. Symp. on Robotic and Sensors Environments (ROSE), Montreal, QC, September 2011, pp. 60–64
[166] Turk, M.A., Pentland, A.P.: 'Face recognition using eigenfaces'. IEEE Computer Vision and Pattern Recognition, Shanghai, March 2011, pp. 586–591
[167] Etemad, K., Chellappa, R.: 'Discriminant analysis for recognition of human face images', *JOSA-A*, 1997, **14**, (8), pp. 1724–1733
[168] Bartlett, M.S., Movellan, J.R., Sejnowski, T.J.: 'Face recognition by independent component analysis', *IEEE Trans. Neural Netw.*, 2002, **3**, (6), pp. 1450–1464
[169] Ojala, T., Pietikainen, M., Maenpaa, T.: 'Multiresolution gray-scale and rotation invariant texture classification with local binary patterns', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2002, **24**, pp. 971–987
[170] Ahonen, T., Hadid, A., Pietikainen, M.: 'Face description with local binary patterns: application to face recognition', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2006, **28**, pp. 2037–2041
[171] Lowe, D.G.: 'Distinctive image features from scale-invariant keypoints', *Int. J. Comput. Vis.*, 2004, **60**, (2), pp. 91–110
[172] Faraji, M.R., Qi, X.: 'Face recognition under illumination variations based on eight local directional patterns', *IET Biometrics*, 2015, **4**, (1), pp. 10–17
[173] Karu, K., Jain, A.K.: 'Fingerprint classification', *Pattern Recogn.*, 1996, **29**, (3), pp. 389–404
[174] Vlad, M.A.R.I.A., Parvulet, R.A., Vlad, M.S.A.: 'Survey of livestock identification systems'. Proc. of 13th WSEAS Int. Conf. on Automation and Information (ICAI), June 2012, pp. 165–170
[175] Kumar, S., Tiwari, S., Singh, S.K.: 'Face recognition for cattle'. Proc. of 3rd IEEE Int. Conf. on Image Information Processing (ICIIP), Waknaghat, 2015, pp. 65–72, doi: 10.1109/ICIIP.2015.7414742
[176] Collins, L.M.: 'Non-intrusive tracking of commercial broiler chickens in situ at different stocking densities', *Appl. Anim. Behav. Sci.*, 2008, **112**, pp. 94–105
[177] Piczak, K.: 'Recognizing bird species in audio recordings using deep convolutional neural networks'. Int. Conf. CLEF Working Notes, 2016, pp. 273–288
[178] Jain, S., Laxmi, V.: 'Analysis and design of neural network based image retrieval system for identification of species'. Int. Conf. on Computation of Power, Energy Information and Communication (ICCPEIC), Melmaruvathur, Chennai, India, March 2016, pp. 188–192
[179] Bressane Roveda, J.A.F., Martins, A.C.G.: 'Pattern recognition in trunk images based on co-occurrence descriptors: A proposal applied to tree species identification'. Latin America Congress on Computational Intelligence (LA-CCI), Curitiba, November 2015, pp. 1–6
[180] Reyes, A.K., Camargo, J.E.: 'Visualization of audio records for automatic bird species identification'. 20th Symp. on Signal Processing, Images and Computer Vision (STSIVA), Bogota, September 2015, pp. 1–6
[181] Kamińska, D., Gmerek, A.: 'Automatic identification of bird species: A comparison between kNN and SOM classifiers'. Joint Conf. on New Trends in Audio & Video and Signal Processing: Algorithms, Architectures, Arrangements and Applications (NTAV/SPA), Lodz, Poland, August 2012, pp. 77–82
[182] Rossi, F., Benso, A., Di Carlo, S., *et al.*: 'A mobile App to detect fish falsification through image processing and machine learning techniques'. IEEE Int. Conf. on Automation Quality and Testing Robotics (AQTR), Cluj-Napoca, May 2016, pp. 1–6
[183] Jill, M.L., Buler, J.J., Frank, R.M.: 'Geographic position and landscape composition explain regional patterns of migrating landbird distributions during spring stopover along the northern coast of the Gulf of Mexico', *Landsc. Ecol.*, 2016, **31**, (8), pp. 1697–1709
[184] Tashakkori, R., Ghadiri, A.: 'Image processing for honey bee hive health monitoring'. SoutheastCon 2015, Fort Lauderdale, FL, April 2015, pp. 1–7
[185] Beyan, C., Fisher, R.B.: 'Detecting abnormal fish trajectories using clustered and labeled data'. 20th IEEE Int. Conf. Image Processing, Melbourne, VIC, September 2013, pp. 1476–1480