Review

Animal biometrics: quantifying and detecting phenotypic appearance

Hjalmar S. Kühl[1] and Tilo Burghardt[2]

[1] Department of Primatology, Max Planck Institute for Evolutionary Anthropology, Deutscher Platz 6, 04103 Leipzig, Germany
[2] Department of Computer Science, University of Bristol, Woodland Road, Bristol, BS8 1UB, UK

Animal biometrics is an emerging field that develops quantified approaches for representing and detecting the phenotypic appearance of species, individuals, behaviors, and morphological traits. It operates at the intersection between pattern recognition, ecology, and information sciences, producing computerized systems for phenotypic measurement and interpretation. Animal biometrics can benefit a wide range of disciplines, including biogeography, population ecology, and behavioral research. Currently, real-world applications are gaining momentum, augmenting the quantity and quality of ecological data collection and processing. However, to advance animal biometrics will require integration of methodologies among the scientific disciplines involved. Such efforts will be worthwhile because the great potential of this approach rests with the formal abstraction of phenomics, to create tractable interfaces between different organizational levels of life.

Animal biometrics: an emerging field that fingerprints phenotypic appearance

The field of animal biometrics (see Glossary) applies formal approaches to represent and detect phenotypic appearance. It can be used to recognize and classify species, identify individuals, detect the occurrence of, or variation in, a particular behavior, as well as to measure morphological traits and their interindividual variation or intraindividual changes over time (Box 1). Animal biometrics utilizes both the variability and uniqueness of coat patterns, vocalizations, movement dynamics, and body morphologies (Figure 1). Existing approaches in this discipline computationally interpret information about the appearance of animals in a systematic way (specifically through algorithmic formalization). In particular, they define the classes of interest in a highly objective, comparable, and repeatable manner. Achieving this goal demands interdisciplinary collaboration between ecologists, engineers, computer scientists, and statisticians.

Animal biometrics expands on a longstanding, widely applied tradition in ecological and evolutionary studies of documenting and indexing animal appearance [1]. Early methodological work dating back to the mid-1900s used ordered sketch collections [2] and photographic records [3,4] that depicted animal appearance or behavior. The first symbolic indexation schemes, such as zebra stripe codes [3], stem from this era, foreshadowing a shift towards formalized representations. Although these documentations helped to objectify phenotypic appearance, they were time consuming to produce, dependent on the skills of the producer, and subject to observer error and bias.

Great progress has been made in the field of automated pattern recognition over the past two decades; algorithms to locate, identify, and classify patterns in audiovisual data are now readily available. Building on this foundation, recent advances in computerized human recognition, surveillance, and biometrics have created a plethora of complex techniques used to locate targets [5], assess movement patterns [6] and pose [7], identify individuals [8], determine behavior [9,10], and evaluate facial expressions [11]. These approaches are highly applicable to animal populations. Moreover, they automatically provide formalized and repeatable measures, independent of a subjective human observer (Box 2).

Although it is only recently that biologists have started to adopt these methods, they have altered fundamentally the way in which ecological and evolutionary researchers can acquire and interpret field data. In fact, semiautomatic photo-identification has become well established in fields such as marine animal observation [12,13], and enables researchers to track thousands of individuals over time and space. This is far beyond what can be achieved manually (Box 1). Even more innovative approaches have started to combine animal biometrics with sensor networks [14] and crowd sourcing to boost the feasibility and impact of schemes to monitor endangered species. For example, the ACONE project [15] analyzed months worth of video data to search for the ivory-billed woodpecker, and online databases, such as the ECOCEAN Whale Shark Photo-identification Library [16], have been able to create tens of thousands of crowd-sourced sighting records.

In addition to the limitations of processing large quantities of data manually, human observers often tend to ignore classification uncertainty, which leads to considerable underestimation of rates of misclassification [17]. Animal biometric systems produce probabilistic output. They allow for explicit setting of the trade-off between confidence of detection correctness (precision) and confidence of detection completeness (recall) (i.e., whether all animals present have been detected). Encouragingly, recent developments have started to incorporate data uncertainty into ecological analysis [18–20].

Corresponding author: Kühl, H.S. (kuehl@eva.mpg.de).

0169-5347/$ – see front matter
 http://dx.doi.org/10.1016/j.tree.2013.02.013

Glossary

Algorithmic formalization: description of an effective method by a finite list of well-defined instructions, such as a computer program.
Animal biometrics: quantified approaches for representing and detecting species, individuals, behaviors, or morphology traits based on measurable phenotypic characteristics.
Annotation: addition of information, such as species name, individual identity, pose information, lighting conditions, or object location, to audiovisual data for facilitating training of animal biometrics software.
Biometric entity: class of phenotypic characteristics (e.g., face or stripe pattern) used as source for constructing a biometric profile.
Biometric profile: information used to represent an individual or group in an information system.
Computer vision: discipline concerned with the automated interpretation of high-dimensional data, such as images to produce numerical or symbolic information (e.g., classifications or decisions).
Crowd sourcing: obtaining recordings, annotations, or other content or services from an online community or other large groups of people, rather than from traditional employees or suppliers.
Deformable models: promising class of mathematical representations applicable to describing organic forms; they capture variations in shape and geometry as part of the model.
Diffeomorphic models: specific class of deformable models that encodes changes of organic forms by smooth transforms (transitions) between different shapes.
Identification: process of retrieving identity by matching an unknown biometric profile against a set of known profiles.
Learning systems: hardware or software systems that can improve performance over time by observing data and supervision by a user.
Local descriptor: compact characterization of a confined spatial or temporal region of an audiovisual recording.
Minutiae: discrete landmarks in fingerprints, such as ridge endings or ridge bifurcations, defined by the local topological structure of the pattern.
Occlusion: the partial or entire coverage of the object of interest.
Pose: the posture and articulation of an animal encountered with regard to the viewpoint of an audiovisual recording device.
Precision: measure of correctness; the proportion of objects retrieved by a classification system that was identified correctly.
Recall: measure of completeness; the proportion of the class of interest that was retrieved and identified correctly.
Rigid object models: mathematical object representations, which capture visual appearance as a set of local part characteristics (e.g., dark eye region or bright forehead region) interconnected as spatially fixed configurations (e.g., fixed distances between parts).
Scalability: ability of an algorithm or animal biometric system to operate over different orders of magnitude (e.g., small vs large populations or small vs large area of pattern).
Scale-invariant feature transform (SIFT): one of the most widely used local descriptors employed automatically to find and relate key landmarks (e.g., a specific point on the coat of a particular zebra) between two or more images.
Sensor networks: spatially distributed autonomous sensors that monitor physical or environmental conditions (e.g., sound, video, or temperature) and pass these data via a network to a main location.
Shape contexts: mathematical representations of a landmark cloud, captured in a set of polar histograms.
Spline fitting: positioning of a deformable 3D model of an animal surface (i.e., the spline) in a 2D image that contains an animal. Once the spline model is aligned with the animal in the image, the coat texture of the animal can be extracted for comparison independent of the animal pose.
Template matching: finding an object (e.g., member of a species) by direct comparison of image regions to one prototypical representation of the object class (e.g., a typical example image of the species).
Tracking: following of objects or movements through several frames of a video.
Training data sets: data collections (e.g., images or videos containing a species) that act as samples for automatically learning characteristics of these data (e.g., visual traits that are distinctive to the species); typically require manual annotation to separate the object of interest (e.g., a particular animal) from background (e.g., vegetation).

One of the many advantages of animal biometrics (Box 2) is standardization of observational data for comparative research. Animal biometrics can provide objective measures that can be used for comparison across individuals, species, and populations much in the same way as in disciplines such as remote sensing, physiology, or genetics. This is achieved by breaking down complex phenotypic appearance into comparable 'units'; for example, configurations of landmark features on coat patterns [21,22] or the spectral signature of locomotion [23] (Figure 1).

Here, we present an overview of recent applications of animal biometrics and highlight current and future developments. We start by describing proven designs and components of animal biometric systems; how they represent and quantify phenotypic information; and how they can be used to detect species, individuals and behavior. Furthermore, we outline promising fields of application and point out challenges in this discipline. Finally, we make recommendations for advancing animal biometrics and how nonexperts can enter this field. Although animal biometrics includes audio and visual systems, as well as other modalities, we place particular emphasis on visual applications.

What are animal biometrics? Computerized systems that recognize phenotypes

The source for data acquisition in animal biometrics is the measurable information displayed due to the anatomy or behavior of a species. Typically, aspects of the appearance of an animal, its movement characteristics, or vocalizations are selected and used as biometric entities [24]. Determining a suitable biometric entity set for an animal in a study population is a difficult task. The chosen traits must be measurable by a recording device, adequately permanent, characteristic of the animal class of interest, and universally displayed throughout the relevant study population (Box 3). Iconic coat patterns, such as stripes on zebras [25] and tigers [22], or spots on cheetahs [21], have been shown to satisfy these criteria when used for visual identification of individuals. However, not all prominently visible features are suitable: injury marks on white sharks [26] are highly salient for instance, yet their uniqueness is short lived and marks heal quickly. This temporal variability clearly limits their biometric use for long-term studies.

Although the suitability of biometric entities requires re-evaluation in most studies, proven designs of automated animal biometric systems all contain five key components: those for sensory data acquisition, pattern detection, pattern matching, storage capabilities, as well as for interfacing with applications or users that utilize the extracted information (Figure 2).

For many biological studies, field conditions require these components to be more rugged and self-reliant than those used in human biometrics [27]. Operation in uncontrolled, remote environments with limited energy supply sets challenging conditions for data acquisition, storage, and processing, in particular (Box 3). Examples include lens condensation inside field cameras (if not filled with helium), destruction of camera traps by termites, chewed power supply cables, and system shutdown due to overheating or power shortage. Therefore, to facilitate robust operation and reduce problems, animal biometric systems are often stripped down to minimalist versions of what would be used in controlled environments. This can be sufficient for many study purposes. For example, measures such as flight velocity [15] or gait type [28] can be extracted from low-quality video and have proven adequate for species identification. In any case, animal biometric systems

Box 1. Example impact of animal biometrics on field ecology

Animal biometric systems are used in field projects for the rapid spatiotemporal localization of species from remote audiovisual recordings and for greatly increasing the number of uniquely identifiable individuals than can be tracked over time and space.

A well-developed visual system that detects African apes, chimpanzees, and gorillas (Figure I), using face detection algorithms achieves classification rates of 89–97% under ideal conditions [38]. This classification rate is a function of both image quality and visibility of ape faces. Classification rates decrease if faces of apes are not visible and, thus, can not be detected. Applying this system to field data from remote video cameras reduces time for species detection in video sequences from thousands of clips and hundreds of hours to a few hours or even minutes depending on the computational resources available. The system output provides details on species, date, time, and location (Figure I). Large amounts of video footage can therefore be processed regularly for studies (e.g., to detect ape occurrence, estimate visitation rates, monitor population trends, or evaluate the degree of chimpanzee-gorilla habitat use overlap).

An excellent example for an animal biometric system that is used for greatly increasing the number of uniquely identifiable individuals is the ECOCEAN Whale Shark Photo-ID Library [16] (Figure I). As a joint effort of more than 3400 researchers, volunteers, and citizen scientists, it has acquired more than 43 000 photos of whale sharks, from which more than 3800 individuals could be identified (http://www.whaleshark.org/). Such a large number of photos cannot be matched manually anymore for identifying individuals. The development and application of this biometric system has considerably increased the number of individuals that can be tracked over time and space.

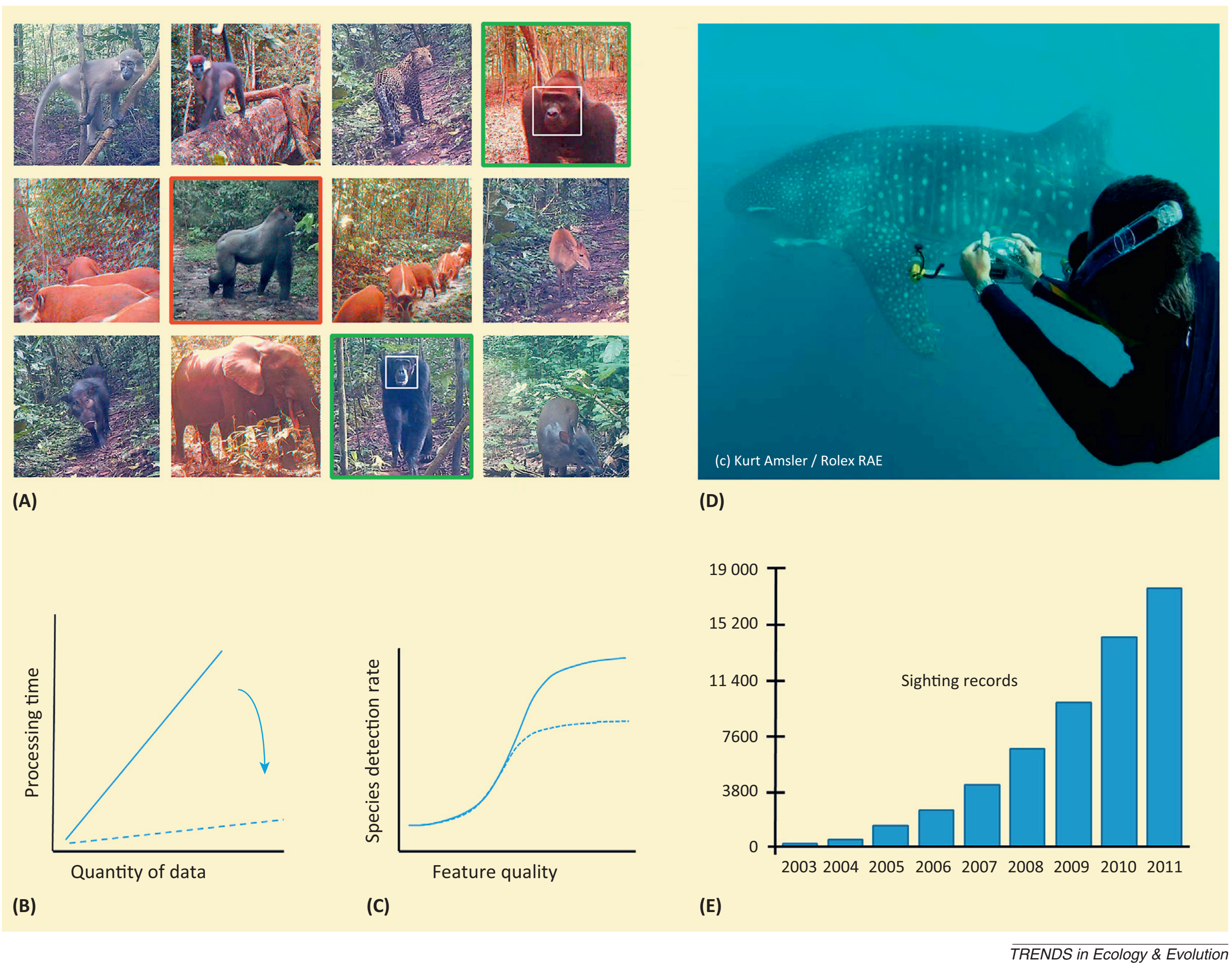
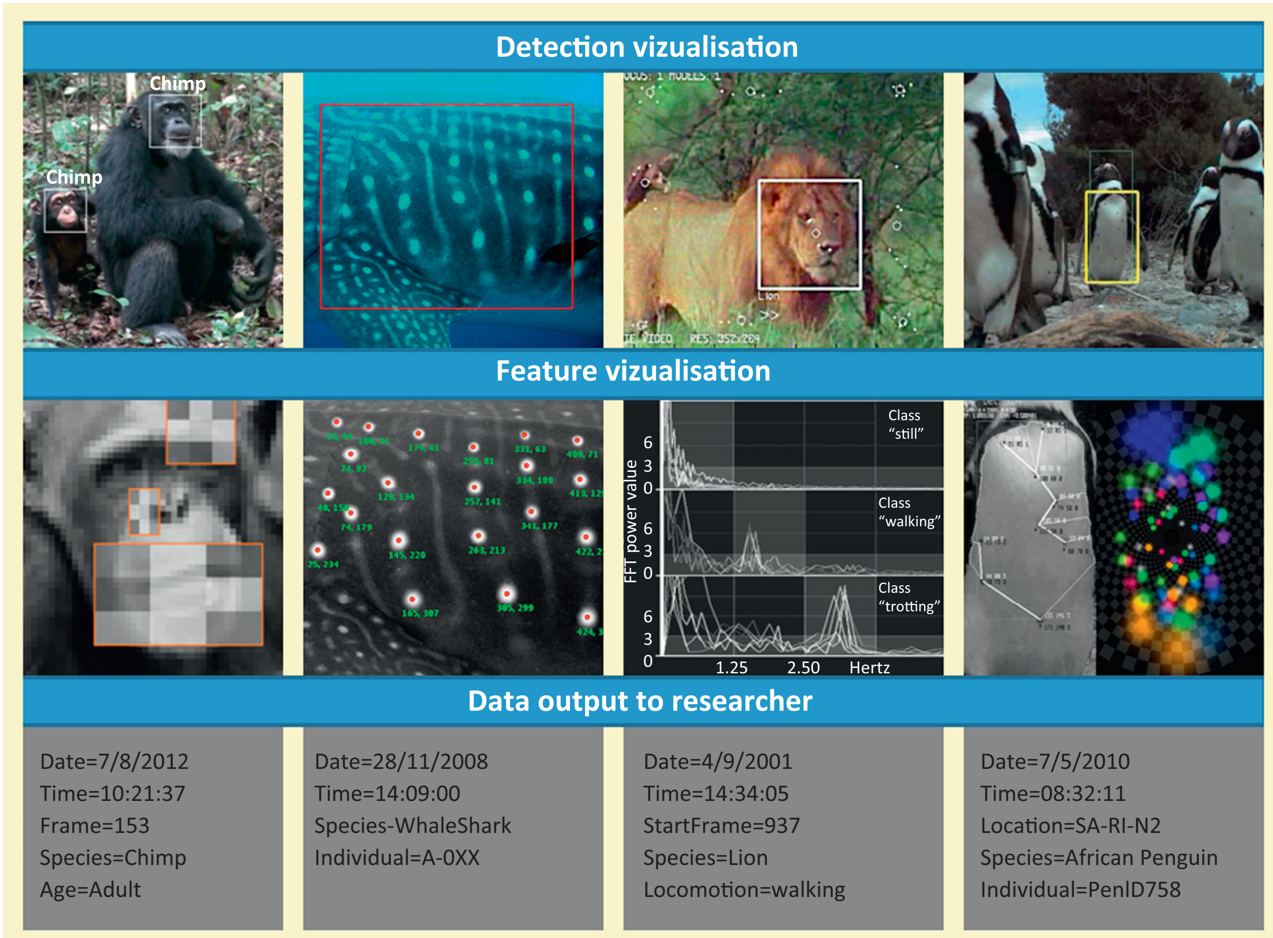


Figure I. Animal biometric systems for species and individual identification. **(A)** Example images taken by camera traps. Depicted are successful chimpanzee and gorilla identifications (bounding boxes, green frames), other animals as well as one missed gorilla (red frame) whose head is not visible. The required processing time for filtering chimpanzee or gorilla footage is orders of magnitude lower than compared to manual processing **(B)**. However, if feature quality is limited or a considerable proportion of ape faces are not visible, a focused human expert will achieve a higher classification rate compared to the animal biometric system (dashed line) **(C)**. Depending on the goal of the study and required spatial and temporal resolution reduced classification accuracy may be offset by time saving or vice versa. **(D)** Diver taking picture of whale shark (crowd-sourcing); **(E)** Increase in number of whale shark sightings documented with photographic records provided to the ECOCEAN Whale Shark Photo-ID Library between 2003 and 2011, from which these data were taken.

identify correspondences of individuals, the same species, or same behaviors among multiple observations.

How do animal biometrics represent phenotypic appearance?

Representing and matching aspects of the phenotype in a quantifiable way is the central algorithmic challenge in animal biometrics. The key difficulty is how to capture the structural complexity exhibited by animal life using models and their parameters: animals actively change their shape and pose; animal surfaces reflect differently under different lighting; and animals frequently appear as partially hidden by other content, such as vegetation (Figures 1 and 2). Although computer graphic models capture some



TRENDS in Ecology & Evolution

Figure 1. Examples of four visual animal biometric systems detecting and classifying species, individuals or behavior. Bounding boxes highlight the detected body parts or morphological traits of interest in video or still images. Visual features used for classification include spatial brightness changes, structural and gradient features (chimpanzee species detection) [38], configuration of spots (individual whale shark identification) [16], spectrum of head motion (lion locomotion recognition) [23], and histograms of spot configurations (individual penguin identification) [43]. Examples are also given of the type of standardized data that is output to the researcher. Whale shark images reproduced with permission of whaleshark.org.

of these aspects accurately, they do not allow for an automatic association between them and input data, such as images or video. For visual systems, the problem can be posed as follows: given a model of an animal and an image, how can one determine which area of the image can be explained by the model (i.e., is the animal of interest in the picture) and under which model parameterization (i.e., what is the pose of the animal etc.). Researchers in computer vision have addressed this problem by developing models that can be related to images efficiently and automatically. Several promising approaches for representation and matching exist (Table S1 in the supplementary material online).

The simplest animal detectors are built using template matching and capture one prototypical instance of overall visual appearance. This can be a representative image of the class of interest, such as an image of a particular 'typical' insect [29] to stand for the whole species. Although easy to generate and straightforward to match against, templates perform poorly when detecting animals under natural conditions.

Tiny or rigid regions of an animal surface, such as a small area of skin, often exhibit less variance compared with the entire organism. In some cases, sets of local descriptors [30,31] such as scale-invariant feature transform (SIFT) [32], have been used for such small regions successfully to represent distinct animal appearance. In scenarios where pose and lighting do not vary, these methods can produce stable identification of rigid body areas [33]. Applications range widely from insect species classification [34] to individual turtle identification [35]. However, these local descriptors disregard global information, such as body structure or observation viewpoint. Consequently, in scenarios where varying appearance, partial occlusion, shadows, or glares cannot be avoided, local descriptors are of limited use.

Rigid object detectors [36] address this by representing appearance as sets of geometrically linked descriptors, describing where features are with respect to each other (Figure 1). Originating from the methods used for human face and pedestrian detection [37], they capture features and their static spatial relationships. Thus, they are capable of integrating information over larger areas of an animal. This technique is suitable for tasks such as animal face detection [38,39], where facial features vary among individuals but their relative configuration remains consistent.

Box 2. Advantages of automated animal biometrics

Several key characteristics of animal biometric systems and their output make them promising and potentially powerful tools for ecological studies [24]. The quantification of animal phenotypic appearance provides a truly objective measure for detecting, discriminating, and identifying species, individuals, and their behavior and morphology. The ability to do this independently of a human observer reduces common sources of variation and bias in human observer studies caused by interpretation subjectivity, skill, or experience. Automated processing facilitates transparency of study results and standardization of methods for analysis. Standardized audiovisual data processing can be replicated reliably for testing repeatable outcomes within and across studies, which is a basic requirement for a study to be considered scientifically rigorous. It facilitates comparisons of studies across individuals, populations, and species in a systematic and objective manner. Autonomous audiovisual recording devices are generally able to collect data continuously through time, compared with limited, discrete time periods of human observers. Increased sample sizes may therefore be collected and processed. Furthermore, studies using well-established automated identification procedures may benefit from the ability to process data sets at considerably higher speeds compared with human observers, which is particularly relevant for tediously repetitive tasks [24]. Researcher performance degrades when conducting repetitive tasks requiring high accuracy for extended periods. Computers are better suited for this kind of data processing; thus, humans can concentrate on the more complex aspects of projects [24]. Freeing human resources for more complex tasks becomes increasingly relevant in budget-limited and data-intensive studies [24].

Box 3. Prerequisites for promising applications

Before launching the development of an animal biometric system for a particular application, it is useful to consider the following four main criteria for evaluating its likely success, potential weaknesses, expected accuracy, and robustness under varying field conditions. First, the degree of differentiation between the classes of interest (i.e., species, individuals, behavior, and morphology) will be fundamental to how accurately automated classification will work. Selected features for class discrimination must be universally exposed within the study population and stable over time. Also, the class of all feature variants needs to be unique enough to separate it from similar feature patterns that are not of interest. These properties determine whether the class of interest can be captured with high probability and low misclassification rate.

Second, the exposure of features of interest in audiovisual source data will determine how well classification algorithms can perform. Occlusion of features of interest and low exposure rates will reduce classification success, whereas constant lighting conditions and shading will facilitate homogeneity of phenotypic appearance. Similarly, the separability of features of interest from background patterns will improve classification rates.

Third, any additional context information that can be used for discriminating classes of interest will increase classification rates. For example, this includes restricting geographic ranges for species, populations, or individuals of interest which might help to reduce the potential classes of interest considerably; the combination of different features, as well as predictable visitation and activity patterns.

Fourth, the technology used for audiovisual recordings will determine how well a system will perform in the long term. Changing environmental conditions may affect the stability of hardware system; user-friendliness, including intuitive use, software stability, and the use of widely accepted data formats and ease of data transfer will improve acceptance by practitioners.

By contrast, advanced visual representations can capture dynamics in deformable models (http://www.pascal-network.org/challenges/VOC/voc2008/workshop/). These models integrate information from different body parts (e.g., along the segments of a movable limb), learning flexible links between them. As with all state-of-the-art approaches, large training data sets containing thousands of manually annotated images and significant computational resources are required to build these models. Other current alternatives, such as spline fitting [22,40], diffeomorphic models [41], or shape contexts [42,43], may be used for detecting flexible animal appearance, but are computationally expensive.

Despite successful applications that have improved both throughput and objectivity of processing tasks, currently no computer vision model for animal biometrics can rival the accuracy of a focused human expert in differentiating species, individuals, or behaviors. The next generation of representational models will begin to incorporate population-wide variance information into the recognition process, as exemplified in projects on 3D human face detection and synthesis [44]. The effort involved will have to be substantial, because model constructions will require extensive 3D population scanning and integration with phenomics to extract population-wide anatomical variation on the level required.

How to use animal biometrics for profiling species and individuals

One of the most frequent applications of animal biometrics is the identification of individual animals. Similarly to the concept of minutiae in human fingerprints [27], uniqueness of animal appearance can typically be encoded by configurations of landmarks. Examples include elephant ear nicks [45], penguin spots [46], zebra stripe junctions [22], or SIFT features for Masai giraffe identification [47]. However, there is a trade-off between pattern variability versus constancy that typically favors either individual identification or species recognition. For example, individually unique information is difficult to extract from patterns that are almost identical across a population, such as insect morphologies [34]. By contrast, highly variable patterns facilitate individual identification [25,33,39,43].

Few fully developed object detection systems for species recognition have made their way out of the laboratory and are being used. The task is complicated not least by the fact that species-specific information is often spatially distributed over various body areas. The few existing implementations either operate on morphologies of limited variance, such as insects [34], or solely make use of distinctive information of the animal head to detect, for instance, cats [48], great apes [38], or other mammals [49].

How to use animal biometrics for profiling behavior

The first automatic methods for behavioral phenotyping of captive mice [50] now exist, allowing for differentiation of behaviors including drinking, grooming, and resting. However, automated animal biometric applications that explicitly extract behaviors are essentially bound to controlled environments. Simplified approaches focus on analyzing footage in wildlife archives [23,51], or consider less complex tasks, such as flock or group movements, as developed for bees [29], fish [52], or birds [53]. Distinctive locomotive activities, such as quadruped gait [28], produce motion

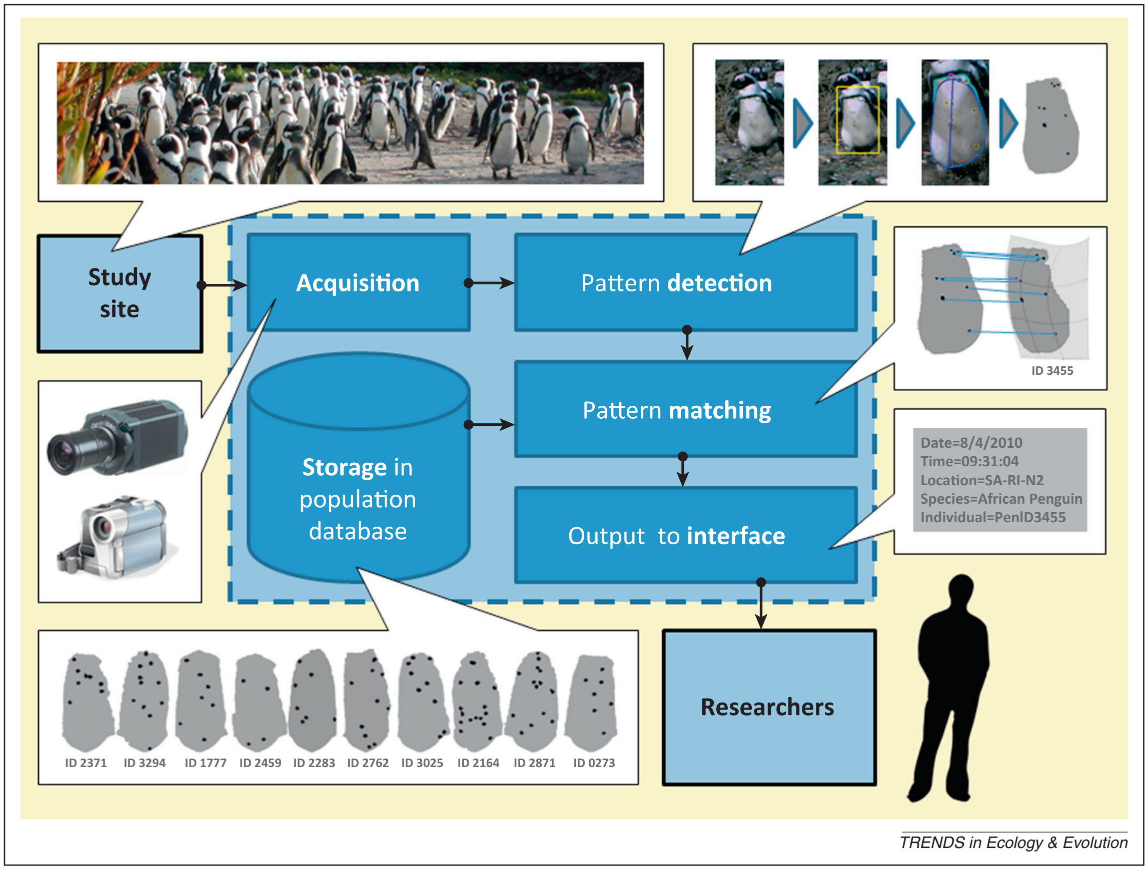


Figure 2. Main components of an animal biometric system. This flowchart summarizes how information from a study site is measured and interpreted for the researcher by an animal biometric system. Each of the components is illustrated, using individual African penguin recognition by spot pattern as an example. Note that system parts can either be connected directly on-site or remotely via networks. Acquisition: automatic or semi-automatic collection of images or video from fixed field cameras, observers or the general public. Detection: the use of computer algorithms to search the images to find those that contain the biometric entity of interest and then to extract relevant information about that entity (e.g., the chest spots of a penguin). Storage: the extracted data on the entity is reduced to a compact mathematical form that can be stored in a suitable database. Matching: the mathematical data on the entity are then compared with other data already stored in the database to find matches that enable the individual or the behavior to be identified, using methods akin to the matching of fingerprints to identify humans. Interfacing: presenting the output of the biometric system to a user or software system for further analysis.

signatures that are sufficient to determine animal presence from video and classify behavior such as walking, trotting, or stalking [23]. Methods in this field have great potential and suitable recognition techniques are abundant [9,10,54–56]. Yet, the development and testing of complex audiovisual behavior detection systems for the wild remain to be implemented.

Opportunities, challenges and recommendations

Promising fields of application

Animal biometric systems have great potential for assisting in the filtering and indexing of audiovisual content that is increasingly produced in many ecological and evolutionary studies [24]. Handheld audiovisual devices, passive acoustic recording devices, and sensors carried by aerial vehicles are being increasingly used to document observations [57–60]. These routinely produce huge quantities of audiovisual data that are often at the limit of what can be processed manually. The time required to sift through the data can be an order of magnitude greater than the actual recording time; animal biometric systems can be of great help by providing information on the precise occurrence of certain species, individuals, their behavior, or morphological patterns of interest in a fraction of this time.

Population surveying and monitoring studies are increasingly making use of technologies such as camera traps and passive audio-recording devices [57]. Here too, animal biometrics has the potential to reduce drastically the time spent analyzing the data. Although a few studies have demonstrated the potential for integrating animal biometrics into such systems [13,61], considerable work remains to integrate animal biometric output fully into existing statistical frameworks and to develop standardized system outputs. Similarly, biodiversity assessments that are increasingly conducted to document and evaluate the impact of human activities or to study questions on community ecology are promising fields of application.

Other applications will be at field sites that routinely collect data on animal ecology and behavior [62–64]. The use of audiovisual recording not only complements the human observer, but also allows for the subsequent use of animal biometric systems to classify, analyze, and archive the data. Observations may be revisited later in much greater detail than is currently possible with other types of documentation, such as coded observations. Furthermore, analysis with animal biometric systems may provide standardized time series data on basic information, such as grouping patterns or interindividual proximity, that can easily be compared between different sites. The application of animal biometric systems in studies on animal morphology can set new standards for measuring changes through the lifetime of an individual, variation within populations or phenotypic plasticity, and responses to environmental fluctuation or change [65]. One of the advantages of animal biometric systems is that they are non-invasive (Box 2). Tagging or collaring animals may itself cause changes along with changes in behavior, reproduction, and survival and, thus, potentially bias observations [66]. Due to their non-invasiveness, animal biometric systems are unlikely to affect animals to any extent.

Eventually, animal biometric systems may provide a solid base to compare and link phenotypic appearance patterns in a standardized way to other organizational levels of life, such as the physiological or genetic constitution of an organism. The rate of progress in the newly emerging field of phenomics [67] will be crucially dependent on the availability of powerful tools to capture and quantify phenotypic appearance. If widely accepted standards for phenotypic appearance data analysis were available similar to those in the genetic and physiological domain, it would considerably advance genotype–phenotype comparisons [53]. Such studies, with free-ranging animals under natural conditions, have yet to be performed.

Community, communication, and data and tool sharing

Animal biometrics is still in its infancy and remains an open field. However, animal biometrics is also a highly interdisciplinary field that requires input from various disciplines to develop truly robust, widely applicable, and useful tools. Therefore, the rate of progress that is made will depend largely on successful collaborations and sharing of expertise among members of the different scientific communities. Communication will be key; for example, computer scientists and engineers will need to articulate clearly what a biometric system can achieve. The clear advantage of automated audiovisual data processing arises when data collection and interpretation are highly repetitive tasks [24] that can be performed quickly by computers but that take a long time for human observers to do. However, it needs to be clearly communicated that this increase in quantity may in turn be offset by uncertainty in the results. For example, when identifying an individual, animal biometric systems produce the most probable match (and can even express the probability that the match is correct); however, many field practitioners, used to seemingly certain output from human observer systems, may feel uncomfortable about the apparent lack of certainty (Box 1). In practise, it should be possible to 'tune' an animal biometric system such that the uncertainty in results is less than the probability of a human error. An additional challenge will be to make well-developed biometric tools easily accessible to specialists and nonspecialists in this field. This may necessitate clear instructions and interfaces for intuitive use, as well as communication on request by the user community (Box 4).

Ecologists and evolutionary biologists, by contrast, need to articulate their needs clearly with regard to species, individual, behavioral, and morphological trait identification. They need to point out the most promising features for species or individual discrimination, or the characterization of behavioral or morphological traits. This will also include the generous sharing of audiovisual recordings, of which large quantities exist, which are generally not openly accessible, yet would be of immediate benefit for developers of animal biometric systems. Ecologists will need to test and evaluate developed systems in an unprejudiced manner to judge whether they indeed provide an advantage in efficiency, accuracy, or comparability over existing human observer methods.

This need to find a common language and communication must be complemented by the generous and open sharing of ideas, data, and algorithms within and between all the scientific communities involved (Box 4). There are already encouraging first signs of a changing research culture, which point to an increased willingness to dissolve traditional boundaries, which often prohibit truly cross-disciplinary work. An excellent starting point to disseminate, publicize, and preserve such information lies in the existing platforms and networks (e.g., Shepherd project; http://www.ecoceanusa.org/shepherd). The further development and maintenance of these networks will be crucial

Box 4. Recommendations for future animal biometric field systems

To advance animal biometrics, develop robust tools and make them widely available to practitioners, the following recommendations are proposed. One of the most critical issues that need to be improved is the generous transfer of systems and knowledge among researchers and practitioners. Animal biometric systems should be made available, even if development has come to an end. Due to the reality of limiting funding cycles, animal biometric systems remain all too often in an imperfect stage after the end of a project and do not enter a phase of critical evaluation by practitioners and subsequent continuous improvement through a fruitful knowledge exchange of users and developers. Although some tool developers already spearhead this effort by sharing their tools generously, more sharing is needed for overcoming this problem. This also includes providing detailed instructions on algorithms and tool applications. Ideally, software is made available as open source for continuous development by the user community. Equally important is a user-friendly system design that facilitates transfer of knowledge contained in such early stage tools. User friendliness will be key for attracting potential users who can help to further promote system dissemination.

Practitioners will always be most critical to systems that are not transparent, difficult to use, and have unreliable results in their output. Their main evaluation criteria will always be the comparison with existing alternative approaches. Therefore, developed systems have to withstand rigorous evaluations and testing under various or alternatively well-defined and documented conditions, in which they are fully functional. Inflating system performance by limiting it to highly invariant laboratory conditions may help publishing it, but may at the same time disappoint users applying the system in very different real-world conditions. Improved knowledge and system transfer could benefit considerably by forming a community of practitioners. This is done best by joint platforms, making developed tools, source code, and application knowledge available, mixing research groups of field practitioners and system engineers to facilitate true crossdisciplinary work, and organizing joint conferences.

Lastly, all of these recommendations should help newcomers in this field to gain easier access to existing tools and knowledge than has been possible before. Newcomers are most likely to succeed if they join existing groups, and gain experience with existing systems to learn about characteristics of the field of animal biometrics and its pitfalls, before embarking on the development of new systems.

Table 1. Examples of existing animal biometric systems for species and individual identification

Projects	Species	Modality	Website	Refs
Conservation Research	Various	Visual	http://www.conservationresearch.co.uk	[22]
ECOCEAN	Whale sharks	Visual	http://www.whaleshark.org	[16]
iBATsID	Bats	Acoustic	https://sites.google.com/site/ibatsresources/home	[73]
PAM	Humpback whales	Acoustic	http://stellwagen.noaa.gov/science/passive_acoustics_current.html	[74]
RBT+ACONE	Various birds	Visual	http://rbt.cse.tamu.edu	[15]
			http://telerobot.cs.tamu.edu/cone	
SAISBECO	Apes	Visual	http://www.saisbeco.de	[38,39]
The APRS	Penguins	Visual	http://www.penguinid.com	[46]

to create a research environment that can inspire the truly crossdisciplinary work required for advancing the field of animal biometrics.

Moving even more broadly and collaboratively, one interesting concept is the use of citizen scientists to contribute voluntarily to research. Examples include the annotation of imagery required for subsequent training of animal biometric systems or the evaluation of system performance. Various projects have successfully demonstrated the utilization of citizen scientists [68–70], and their involvement to classify audiovisual recordings is only the next step.

Technological challenges

The animal biometric systems that exist today use a broad spectrum of methods for acquisition, detection, matching, storage, and interfacing (Figure 2). This diversity of approaches often prohibits their transferability across studies, which, ironically, is one of the goals of animal biometrics. Identifying common approaches and introducing more modular system designs, customizable to individual studies, is a critical goal to make solutions more generic, and cheaper to produce and maintain. Any move towards this goal will help to standardize the field and promote its wider application. Particular algorithmic challenges lie in coping with variable lighting, partial occlusion, complex organic deformation, and the need to annotate manually large image sets to train methods. Current advances in computer vision modeling and machine learning [71] promise to address this challenge.

Unifying the structure of output data is particularly critical because it is the key interface between the system and the researcher. Standardization of output structure will help newcomers to utilize systems more quickly, promote system comparability and interaction, as well as generate system attractiveness, acceptance, and understanding.

Although considerable progress has been made in incorporating knowledge on misidentification error rates into ecological data analysis [19,20], further intricate extensions to existing statistical tools are required to integrate animal biometric output fully. Novel opportunities could lie in trading spatial for temporal resolution to estimate density. For instance, camera traps provide high temporal resolution, but usually cover only a small area. Nevertheless, such a scenario can be used to estimate population density. Adjusting capture–mark–recapture (CMR) methods for using uncertain sighting data beyond the state-of-the-art is also likely to attract increasing interest [19,20,72]. To create the most efficient systems will require careful consideration of workflows [16], so as to provide a seamless integration of human and machine capabilities.

Concluding remarks, recommendations, and outlook

The emerging field of animal biometrics is on the verge of providing powerful tools for field practitioners, ecologists, and researchers to use to collect and process phenotypic appearance information on species, individuals, their behavior, and morphology, in a standardized way and for a broad spectrum of applications. Although existing systems have shown that animal biometrics are feasible and useful to the biologist (Table 1); numerous challenges lie ahead to develop the field into a widely accepted and applied subject. Bridging the gap between the different disciplines involved remains the greatest challenge.

To achieve major impact, the applicability of animal biometrics needs to be widened. Interesting ideas include robotic systems (e.g., drones) that actively seek data by traversing the habitat to increase both the quality and quantity of acquired data and learning systems that adapt better to highly unpredictable environments, continuously improving on system capabilities.

Although animal biometric systems are of use for a wide range of disciplines, they may show their greatest potential in the emerging field of phenomics. Formalized phenotypic appearance information is key for linking the phenotype of an organism to other organizational levels of life and, thus, for integrating closely interacting biological processes: to the genetic and physiological constitution of an organism, to the dynamics of populations, or to the interactions of communities.

The complexity of the system design challenge ahead calls for a new breed of biologically knowledgeable engineers and technically inspired biologists. These should be crossdisciplinary scientists who have an intimate 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 revolutionizing the way we look at the phenotype.

Acknowledgments

This contribution is an output of SAISBECO, a joint project by Fraunhofer IDMT and IIS, Max Planck Institute for Evolutionary Anthropology, and the Visual Information Laboratory at the University of Bristol. We thank the providers of images (Kurt Amsler, Tobias Deschner, Karsten Dierks, Andreas Ernst, Jojo Head, Brad Norman, and Luisa Rabanal) and the Pan African Program. We are grateful to Doug

Bolger and an anonymous reviewer for providing highly constructive feedback, and Peter Barham, Rachel Jackson, Martha Robbins, Carolyn Rowney, and Cathy Crockford for very helpful comments on the manuscript and for editing it.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.tree.2013.02.013.

References

1 Prodger, P. (2009) *Darwin's Camera: Art and Photography in the Theory of Evolution*, Oxford University Press
2 Scott, D.K. (1978) Identification of individual Bewick's swans by bill patterns. In *Animal Marking: Recognition Marking of Animals in Research* (Stonehouse, B., ed.), pp. 160–168, MacMillan
3 Klingel, H. (1974) Social organisation and behaviour of the Grevy's zebra. *Z. Tierpsychol.* 36, 36–70
4 Mizroch, S.A. and Harkness, S.A.D. (2003) A test of computer-assisted matching using the North Pacific humpback whale, Megaptera novaeangliae, tail flukes photograph collection. *Mar. Fish. Rev.* 65, 25–37
5 Felzenszwalb, P. *et al.* (2010) Object detection with discriminatively trained part based Models. *IEEE Trans. Pattern Anal. Mach. Intell.* 32, 1627–1645
6 Moll, G.P. *et al.* (2011) Outdoor human motion capture using inverse kinematics and von Mises-Fisher sampling, In *IEEE '11: Proceedings of the 2011 International Conference on Computer Vision*, pp. 1243–1250
7 Shotton, J. *et al.* (2011) Real-time human pose recognition in parts from single depth images, In *CVPR '11 Proceedings of the 2011 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1297–1304
8 Kumar, R. (2012) Trainable convolution filters and their application to face recognition. *IEEE Trans. Pattern Anal. Mach. Intell.* 34, 1423–1436
9 Poppe, R. (2010) A survey on vision-based human action recognition. *Image Vis. Comput.* 28, 976–990
10 Wang, L. and Suter, D. (2007) Learning and matching of dynamic shape manifolds for human action recognition. *IEEE Trans. Image Process.* 16, 1646–1661
11 Pfister, T. (2011) Differentiating spontaneous from posed facial expressions within a generic facial expression recognition framework, In *2011 IEEE International Conference on Computer Vision: Workshops*, pp. 868–875
12 Marshall, A.D. and Pierce, S.J. (2012) The use and abuse of photographic identification in sharks and rays. *J. Fish Biol.* 80, 1361–1379
13 Speed, C.W. *et al.* (2007) Spot the match: wildlife photo-identification using information theory. *Front. Zool.* 4, 2
14 Ahmadian, S. (2010) Heartbeat of a nest: using imagers as biological sensors. *ACM Trans. Sens. Netw.* 6, 19
15 Song, D. *et al.* (2008) System and algorithms for an autonomous observatory assisting the search for the ivory-billed woodpecker, In *IEEE International Conference on Automation Science and Engineering*, pp. 200–205
16 Holmberg, J. *et al.* (2009) Estimating population size, structure, and residency time for whale sharks *Rhincodon typus* through collaborative photo-identification. *Endangered Species Res.* 7, 39–53
17 Guschanski, K. *et al.* (2009) Counting elusive animals: comparing field and genetic census of the entire mountain gorilla population of Bwindi impenetrable National Park, Uganda. *Biol. Conserv.* 142, 290–300
18 Wright, J.A. *et al.* (2009) Incorporating genotype uncertainty into mark recapture-type models for estimating abundance using DNA samples. *Biometrics* 65, 833–840
19 Yoshizaki, J. *et al.* (2009) Modeling misidentification errors in capture-recapture studies using photographic identification of evolving marks. *Ecology* 90, 3–9
20 Morrison, T.A. *et al.* (2011) Estimating survival in photographic capture–recapture studies: overcoming misidentification error. *Methods Ecol. Evol.* 2, 454–463
21 Kelly, M.J. (2001) Computer-aided photograph matching in studies using individual identification: an example from Serengeti cheetahs. *J. Mammal.* 82, 440–449
22 Hiby, L. *et al.* (2009) A tiger cannot change its stripes: using a three-dimensional model to match images of living tigers and tiger skins. *Biol. Lett.* 5, 383–386
23 Burghardt, T. and Calic, J. (2006) Real-time face detection and tracking of animals, In *IEEE 8th Seminar on Neural Network Applications in Electrical Engineering*, pp. 27–32
24 Gaston, K.J. and O'Neill, M.A. (2004) Automated species identification: why not? *Philos. Trans. R. Soc. Lond. B* 359, 655–667
25 Lahiri, M. *et al.* (2011) Biometric animal databases from field photographs: identification of individual zebra in the wild, In *Proceedings of the 1st ACM International Conference on Multimedia Retrieval*, pp. 6
26 Domeier, M.L. and Nasby-Lucas, N. (2007) Annual re-sightings of photographically identified white sharks (*Carcharodon carcharias*) at an eastern Pacific aggregation site (Guadalupe Island, Mexico). *Mar. Biol.* 150, 977–984
27 Wayman, J. *et al.*, eds (2005) *Biometric Systems: Technology, Design and Performance Evaluation*, Springer
28 Hannuna, S. *et al.* (2005) Identifying quadruped gait in wildlife video, In *IEEE International Conference on Image Processing*, pp. 713–716
29 Kranner, I. and Bischof, H. (2011) Stereoscopic motion analysis in densely packed clusters: 3D analysis of the shimmering behaviour in giant honey bees. *Front. Zool.* 8, 3
30 Mikolajczyk, K. and Schmid, C. (2004) A performance evaluation of local descriptors. *IEEE Trans. Pattern Anal. Mach. Intell.* 2, 257–263
31 Wang, Z. and Fan, B. (2011) Local intensity order pattern for feature description, In *IEEE International Conference on Computer Vision*, pp. 603–610
32 Lowe, D.G. (2004) Distinctive image features from scale-invariant keypoints. *Int. J. Comput. Vis.* 60, 91–110
33 Dietterich, T.G. (2009) Machine learning in ecosystem informatics and sustainability, In *Proceedings of the 21st International Joint Conference on Artificial Intelligence*, pp. 8–13
34 Larios, N. (2008) Automated insect identification through concatenated histograms of local appearance features. *Mach. Vis. Appl.* 19, 105–123
35 de Zeeuw, P.M. (2010) Computer assisted photo identification of Dermochelys coriacea, In *Proceedings of International Conference on Pattern Recognition 2010*, (http://oai.cwi.nl/oai/asset/17164/17164D.pdf)
36 Dalal, N. and Triggs, B. (2005) Histograms of oriented gradients for human detection, In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 886–893
37 Viola, P. *et al.* (2003) Detecting pedestrians using patterns of motion and appearance, In *Proceedings of the Ninth IEEE International Conference on Computer Vision*, pp. 734–741
38 Ernst, A. and Küblbeck, C. (2011) Fast face detection and species classification of African great apes, In *Proceedings of the 8th IEEE International Conference on Advanced Video and Signal-Based Surveillance*, pp. 279–284
39 Loos, A. and Pfitzer, M. (2012) Towards automated visual identification of primates using face recognition, In *19th International Conference on Systems, Signals and Image Processing*, pp. 425–428
40 Hiby, L. and P. Lovell (1990) Computer-aided matchings of natural markings: a prototype for grey seals, In *Report of the International Whaling Commission*, pp. 57–61
41 Yang, C.M. and Ravela, S. (2009) Deformation invariant image matching by spectrally controlled diffeomorphic alignment, In *IEEE 12th International Conference on Computer Vision*, pp. 1303–1310
42 Belongie, S. *et al.* (2001) Shape matching and object recognition using shape contexts. *IEEE Trans. Pattern Anal. Mach. Intell.* 24, 509–522
43 Sherley, R.B. *et al.* (2010) Spotting the difference: towards fully-automated population monitoring of African penguins *Spheniscus demersus*. *Endangered Species Res.* 11, 101–111
44 Blanz, V. and Vetter, T. (2003) Face recognition based on fitting a 3D morphable model. *IEEE Trans. Pattern Anal. Mach. Intell.* 25, 1063–1074
45 Ardovini, A. *et al.* (2008) Identifying elephant photos by multi-curve matching. *Pattern Recognit.* 41, 1867–1877
46 Burghardt, T. and Campbell, N. (2010) Generic phase curl localisation for an individual identification of Turing-patterned animals. In *VAIB Workshop at 20th International Conference in Pattern Recognition*, pp. 17–21

47 Bolger, D.T. *et al.* (2012) A computer-assisted system for photographic mark–recapture analysis. *Methods Ecol. Evol.* 3, 813–822
48 Zhang, W. (2008) Cat head detection: how to effectively exploit shape and texture features. *Lect. Notes Comput. Sci.* 5305, 802–816
49 Zhang, W. *et al.* (2011) From tiger to panda: animal head detection. *IEEE Trans. Image Process.* 20, 1696–1708
50 Jhuang, H. *et al.* (2010) Automated home-cage behavioural phenotyping of mice. *Nat. Commun.* 1, Article 68
51 Ramanan, D. *et al.* (2006) Building models of animals from video. *IEEE Trans. Pattern Anal. Mach. Intell.* 28, 1319–1334
52 Papadakis, V.M. (2012) A computer-vision system and methodology for the analysis of fish behaviour. *Aquac. Eng.* 46, 53–59
53 Tweed, D. and Calway, A. (2002) Tracking many objects using subordinated condensation, In *Proceedings of the British Machine Vision Conference*, pp. 283–292
54 Reilly, V. *et al.* (2010) Detection and tracking of large number of targets in wide area surveillance, In *Proceedings of the 11th European Conference on Computer Vision Part III*, pp. 186–199
55 Wu, S. *et al.* (2010) Chaotic invariants of Lagrangian particle trajectories for anomaly detection in crowded scenes, In *Conference on Computer Vision and Pattern Recognition*, pp. 2054–2060
56 Collins, L.M. (2008) Non-intrusive tracking of commercial broiler chickens *in situ* at different stocking densities. *Appl. Anim. Behav. Sci.* 112, 94–105
57 Ahumada, J.A. *et al.* (2011) Community structure and diversity of tropical forest mammals: data from a global camera trap network. *Philos. Trans. R. Soc. Lond. B* 366, 2703–2711
58 Buckland, S.T. *et al.* (2012) Aerial surveys of seabirds: the advent of digital methods. *J. Appl. Ecol.* 49, 960–967
59 Watts, A.C. *et al.* (2010) Small unmanned aircraft systems for low-altitude aerial surveys. *J. Wildl. Manage.* 7, 1614–1619
60 Damm, P.E. *et al.* (2010) Variation in detection among passive infrared triggered-cameras used in wildlife research. *Proc. Annu. Conf. Southeast Assoc. Fish Wildl. Agencies* 64, 125–130
61 Yang, J. (2011) The thin plate spline robust point matching (TPS-RPM) algorithm: a revisit. *Pattern Recognit. Lett.* 32, 910–918
62 Clutton-Brock, T.H. and Sheldon, B.C. (2010) Individuals and populations: the role of long-term, individual-based studies of animals in ecology and evolutionary biology. *Trends Ecol. Evol.* 25, 562–573
63 Kappeler, P. and Watts, D. (2011) *Long-term Field Studies of Primates*, Springer
64 Magurran, A.E. *et al.* (2010) Long-term datasets in biodiversity research and monitoring: assessing change in ecological communities through time. *Trends Ecol. Evol.* 25, 574–582
65 Pérez-Rodríguez, L. *et al.* (2013) Fractal geometry of a complex plumage trait reveals bird's quality. *Proc. R. Soc. B* 280, 20122783
66 Saraux, C. *et al.* (2011) Reliability of flipper-banded penguins as indicators of climate change. *Nature* 469, 203–206
67 Houle, D. *et al.* (2010) Phenomics: the next challenge. *Nat. Rev. Genet.* 11, 855–866
68 Cohn, J.P. (2008) Citizen science: can volunteers do real research? *Bioscience* 58, 192–197
69 Silvertown, J. (2009) A new dawn for citizen science. *Trends Ecol. Evol.* 24, 467–471
70 Hochachka, W.M. *et al.* (2012) Data-intensive science applied to broad-scale citizen science. *Trends Ecol. Evol.* 27, 130–137
71 Coates, A. *et al.* (2012) Emergence of object-selective features in unsupervised feature learning. *Adv. Neural Infor. Process. Syst.* 25, 2690–2698
72 Constantine, R. *et al.* (2012) Abundance of humpback whales in Oceania using photo-identification and microsatellite genotyping. *Mar. Ecol. Prog. Ser.* 453, 249–261
73 Walters, C.L. *et al.* (2012) A continental-scale tool for acoustic identification of European bats. *J. Appl. Ecol.* 49, 1064–1074
74 Van Parijs, S.M. *et al.* (2009) Mesoscale applications of near real-time and archival passive acoustic arrays. *Mar. Ecol. Prog. Ser.* 395, 21–36