Review of the Current Research in Animal Individual Recognition

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Abstract

With the development of biological identification for human beings, it also develops such as fingerprint, facial recognition, and iris identification. Scientists and zoologists must be more content with the cumbersome ways of identifying previously existing animals. Old methods such as ear cutting, chip implantation, and nose print recognition harm animals and humans. It has to catch the animals or needed professionals for individual identification (e.g, identify sharks by taking photos of their fins). Therefore, more and more scientists and engineers are trying to develop more efficient methods for individual animal identification. Of course, there are also many very constructive cases. Thus, this literature review will provide information about three regions of the latest recognition technology: radio-frequency identification (RFID), animal facial identification, and iris recognition.

Keywords: ***animal, identification, facial recognition, iris recognition, radio frequency identification (RFID), convolutional neural networks (CNNs).***

1. Introduction

Speaking of the progress of animal identification, it seems inescapable to mention the history of human identification. By only looking at the way our mobile phone locks it can reflect individual identification. From the earliest passcode, we transfer to biological recognition methods which is the fingerprint then on to the now popular face recognition. However, for most people, the latest identification of an animal is limited to the microchip in the body of their pets or even the ear tag on the cow. Since more and more people recognised the importance of protecting our environment and animals, therefore animal identification technology seems like a major area that can help with conservation.

There are two different situations for the current biological recognition technology. First, most of the research in animal identification methods is still testing in the agricultural region which is easy to collect data and capture signals/images (e.g RFID and noise). However, this also reflects the fact that these technologies have not yet been used outside of their "comfort zone" because of light or signal problems in nature. Then there are those technologies that are already well established but the disadvantage with them is that they are invasive (e.g microchip, GPS, etc.) which is obviously not suitable for those animals in the wild.

Our literature review mainly introduces and analyzes three technologies that we believe are currently the most prominent in the field of animal recognition and have the most development prospects in the future, namely radio-frequency identification (RFID), animal facial identification and iris recognition. We present the practical application of these three techniques in the latest research articles and their results in our review. What is more significant is that we not only review on these three animal recognition technologies, but also point out the problems and challenges they may encounter in their use, due to the defects that now exist in those three technologies. Then, we provide several possible solutions for these technologies to solve the problems that researchers may encounter in the future. However, since this review will mainly focus on facial, iris and radio-frequency identification, these will not review this in detail but to give you a brief understanding on the latest developments in these three areas. Thus, we believe that our advice and analysis can be useful to future researcher in the field of animal recognition.

2. Radio Frequency Identification

2.1 *Brief introduction*

Radio Frequency Identification (RFID) is a technology that uses radio waves to passively identify a tagged object. Akhilesh Kumar Singh et.al (2013) asserts that in India RFID technology become essential for dairy farms' animal identification. The use of RFID can maximize farmers' productivity, improving the automatic data collection that provides quick access to dairy herd information and utilized for improving the feeding and managemental practices. This can enhance farm management capabilities. It can be used in to trace cattle movements, and locate individual cows with a single program. Thus, farmers can cater more cows or have more time on other activities [1].

2.2 *Radio Frequency Identification using Ultra High Frequency*

RFID can also adopt new, more flexible and efficient technologies. Ultra-High Frequency (UHF) radio frequency identification (RFID) system is considered viable alternative, with well practices in the food chain or the industry of livestock breeding. Gomes and Shimizu et.al conclude that in 2013, the Brazilian state of Mato Grosso do Sul used the technology to monitor animals. In this project, the operating frequency of UHF RFID was between 860 - 960 Mhz. All the information which are collected would be sent to a central system. During the identification, the information, such as the animal's sex, breed, age and owner was all recorded on the animals' ear tags chips and were sent to the central system. The identification work began in 2013 and ended in 2017. In four years' time, more than 1,000,000 animals were identified through this technology. The UHF-RFID technology has large storage of data in the ear tags and provide more flexibility in the reading possibilities [2].

RFID has different frequencies, low frequency (LF), high frequency (HF) and ultra-high frequency (UHF). UHF RFID is based on passive transponders and does not require batteries. Comparing to other RFID frequencies, UHF RFID is more flexible, having a read range of up to 12 m, and being able to detect more than 100 animals per second. However, the read range and pattern of UHF transponder antennas can be influencsd by water and animal body tissue. And metal can also strongly affect reader antennas. Therefore, the UHF RFID system needs to be thoroughly adjusted and tested in the new application environment [3].

Adrion et.al conducted an experimental scientific evaluation of an RFID system to figure out in a commercial environment what the results will be if they monitor group-housed animals. The first experiment they did was to examine and optimize the pattern and functionality of the UHF RFID system, and the second experiment was to figure out the comparison between UHF RFID system and other sensor systems. In the first experiment, they installed UHF cable antennas in a barn's feed fence compartment, which covered a long section of feed fence with just one antenna. They used two different types of transponder ear tags to test the experiment. Type A consisted of a transponder with a planar inverted-F (PIF) antenna. Model B is a functional model provided by Scot EID Livestock. It is enclosed in an inflatable bag, moulded onto a 50 × 30 mm2 label. It's encased in an air-filled pocket that's molded over a regular plain cow ear tag. In the second part of the experiment, they compare the UHF RFID system with two other systems, the system with nose-band pressure sensor and the system with nose-band pressure sensor. And they detected that the rate of type B tags were higher than type A in one part of the experiment. In the second part of the experiment, the results showed that the average hourly time that the UHF RFID system spent was shorter than the time spent eating recorded using the nose strap sensor; on the other hand, in the comparison to the data of location, the UHF RFID system took longer time to measure. Therefore, they believed that this study showed that UHF RFID still had been more flexible in monitoring animal behaviour in various applications. However, in a barn, it can be challenging to set up UHF RFID antennas, and the effect of surrounding metal is obvious. So they confirmed that comprehensive test was necessary to be applicated in new environment. However, they suggest that the technology, UHF RFID can yet be more flexible to monitor animal behaviours comparing to those identification using other frequencies. The use of UHF RFID system is still promising [3].

3. Identification through appearance

3.1 *Brief introduction*

Facial recognition is already a universal access technology for humans. Undoubtedly, it is one of the most convenient and practical ways to identify every human being. Facial recognition was invented earliest in 1964 by Woody Bledsoe, Helen Chan Wolf, and Charles Bisson, they mark eye centres, nose, and mouse and calculate the distance between them [4]. Even Though the accuracy is extremely low, it proves that facial recognition is a possible way to replace traditional 'keys' and 'locks'. method. In 1988, Sirovich and Kirby began applying linear algebra to the problem of facial recognition, and after Turk and Pentland found out the way to detect faces in an image this technology is rapidly developing like a rocket. In 2017, when mobile phone companies like Apple, Samsung, and Huawei started to use this technology, this not only helped to popularise facial recognition in different scenes and has also brought a lot of convenience to people.

The method to identify each animal is similar to the way we used to recognize each human. They all follow the same steps which are data collecting, modelling, and finally matching. Here comes a question, why is animal appearance technology still at a developing stage while the human facial has already been widely used? Firstly, is about the environment, the main part of facial recognition is the camera, therefore when applied this technology in a wild area it is extremely hard to control the light, also the different environment makes the work even harder since most of the animals who are living in their habitat are hard to detect. Secondly, except for those primates, the facial features of other animals are difficult to distinguish with machines.

3.2 *Facial recognition through CNN*

Convolutional Neural Network (CNN) is a well-known deep learning architecture inspired by the natural visual perception mechanism of the living creatures[5]. They are mimicking the processing of the human brain and this technology is now used for picture/object/facial identification. CNN has several layers to classify the object. Just like humans, we use the features on each person's face to recognize people, and so do machines, but they use algorithms to work out the distance between eyes and eyes, and the distribution of the five senses. There are several different types of CNN systems, here we can use the VGG(visual geometry group) 16 architecture, which is not only one of the most commonly used CNN systems in the recent past but is also used in the identification of Chimpanzees which will be explained later, as an example of how it works. Each CNN system has its advantage for VGG: it can reduce parameters, reduce computation and increase depth.

Table 1. ConvNet Configuration [1409.1556]

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
Input(224x224RGB image)					
conv3-64	con3-64 LRN	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 conv1-256	conv3-256 conv3-256 conv3-256	conv3-256 conv3-256 conv3-256 conv3-256
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 conv1-512	conv3-512 conv3-512 conv3-512	conv3-512 conv3-512 conv3-512 conv3-512
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 conv1-512	conv3-512 conv3-512 conv3-512	conv3-512 conv3-512 conv3-512 conv3-512
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Table 1, shows 6 different types of models and because of the increasing number of layers it gets deeper from left to right, all of them have 5 different blocks and 3 dense layers, and as it goes from block 1 to block 4 the number of channels doubled and block 5 has the same number of filter size. In the training stage, they make the input image (of desired objects to be identified) to a fixed size which is 224x224 and train it more deeply by letting the images get many times of random RGB shifts and horizontal rotations.

Simonyan and his team use 3x3 convolution layers to minimise parameters to learn Use VGG-16 as an example (which is exactly the one used in the study of Chimpanzees recognition), it first starts with an image of 224x224, then blocks 2 halved to 112 x 112, block 3 it halved again, vice versa [6]. Until it reduces to size 7. Therefore, Max pooling is carried out by reducing the size of images and doubling the number of filters. Finally, after 16 layers of filtering, the input image will match the result that has the highest expected rate among all the possible results.

For example, an experiment done by Arsha Nagrani and his team which is about facial recognition for 23 chimpanzees with an overall 92.5% accuracy shows the potential of animal face tracking and recognition. They first collected 10 million face detection of different chimpanzees and used a convolutional neural network system that can track and identify specific chimpanzees and even their gender. What's more this system can also be identified through every viewpoint of the chimpanzee. ' if only frontal faces were used, then the identity recognition accuracy improves to 95.07% and the sex recognition accuracy to 97.36%' [7].

To identify these 23 chimpanzees, Schofield and his team create 23 individual classes and 1 additional class for false positives to increase the accuracy. What's more, in order to make this system more sensitive to the chimpanzees that they test on, a 1.9 hours movie which consists of about 100 non-related chimpanzees were used to train the system.

$$L=-\sum_{n=1}^{N}\left(y_c(x_n)\text{-}\log\sum_{j=1}^{C_t}e^{yj}(x_n)\right) \tag{1}$$

Schofield and his team trained the CNN through this formula to minimise the cross-entropy of the 25 classes (23 individuals, 1 false positive , 1 negatives) , 'where xn is a single face input to the network, yj is the pre-softmax activation for class j of size Ct, and c is the true class of xn.'[7]. Then use a binary cross entropy loss over female and male.

Surprisingly the accuracy of identification by the technology is much higher than the one done by humans. According to the experiment Arsha Nagrani and his team did, the accuracy of identification for people familiar with this chimpanzee is only 40%. Another experiment done by Mark.F. Hansen and his team using CNN methods to identify breeding pigs, came up with an accuracy of 96.7% again demonstrating the viability of this technology across species. Therefore, this again shows the power of technology and the practicability of this method.

More recently, animal identification has been upgraded to include non-primate animals. The BearID made by Melaine Clapham and her team uses only 4675 images of 132 bears to reach an identification accuracy of 83.9% [8]. From primates to non-primates, from 10 million photos to 4,675 photos, this is a qualitative leap forward in animal facial recognition. In this study Melaine Clapham and her team use ResNet-34 architecture which is another CNN system, but it is similar to VGG which explained above. The steps to code a CNN system for bear recognition are much more difficult than for chimpanzees. Since the bear's face will be more defined, his side and front can be completely different. However, the success of this project proved that CNN can be applied on many different animal species, again showing the potential of facial identification.

The convolutional neural network system has a disadvantage which is the accuracy is based on the database it collects, therefore it can work well with zoo or agricultural animals (such as pigs) but it will have lower accuracy when applied to rare wild animals [9]. What's more, it is still questionable whether humans can design a machine that can discriminate between species and individuals at the same time. However, if one day we made it, it is beneficial to our conservation and agricultural development. Especially in the area of animal protection, if we successfully build facial recognition people don't need to install any GPS on animals or capture them just for identification. If technology is further developed, we can even use only a camera to know his age and body injuries. In conclusion, the development of facial recognition for animals still has a long way to go but it is absolutely a region that is worth developing.

4. Identification through iris

4.1 Brief introduction

The pattern of the iris will always count as a stable characteristic of every living organism because unlike facial appearance they rarely change and are always exposed. What's more, finding the difference between subtle gaps in small objects is one of the handiest areas that technologies are good at. They might not be able to find out you got your haircut when you provided an image of your whole body, but they will successfully find out you've worn your fingers out when it is reading your fingerprint. Therefore, the iris identification through either a person or animal individual will have high accuracy, but obviously, there still have a lot of weaknesses that we need to overcome.

Although each animal and human have a unique iris, the idea of Iris identification only emerged not until 1986. 'The upswing of iris recognition as an identification method came just after the millennium when patents expired and the technology was ready for broad commercialization' [10]. People will use infrared light to read your iris and each iris has its unique mathematics patterns.

4.2 Case study

In 2016 Parthasarathi and Dibyendu investigated the iris recognition of gots which is one of the most common livestock all over the world. What's interesting in this study is that compared to other living animals, gots have a rectangular-shaped iris. The recognition accuracy of up to 97.85% also shows the potential in iris recognition [11].

The iris database of each goat is made up of characteristics like freckles, coronas, stripes, furrows, crypts, etc. There are 4 major steps to analyzing an iris, firstly we need to let the camera extract the iris of the goat which also includes the removal of eyelashes (which act as noise to the identification), the author does this through the acquisition of 700 goats eye photo and trained the recognition system with it. Then, the normalization which is also the most important step is to make sure all the iris that has been detected are in the 'same constant dimension' removing the effects of different spaces and environments on the iris state [12]. Then in the iris analysis, Matlab code will be used to find the distance and location of every small feature. They also used the Fourier domain feature of each iris which let the 3d form of each iris be considered.

Moreover, the writer provides a table (table 2) of results that contains the investigation of the iris study in the past few years. According to this table, we can conclude that Iris recognition has a very high accuracy all of them reach above 95%.

Table 2. The Iris Study [1877-0509]

Authors	Recognition Rate	Equal Error Rate	False Acceptance Rate	False Rejection Rate
Daugman	99.9	0.95	0.01	0.09
Boles	94.33	8.13	0.02	1.98
Wildes et al.	95.10	1.76	2.4	2.9
LaborMasek	96	1.72	1.84	2.0
Avila	97.8	3.3	0.03	2.08
Rai	99	0.92	0.03	0.03

Iris recognition utilises the rich individual features in the iris texture, while periocular biometrics utilize the features of the entire eye area, which does not provide very good recognition accuracy compared to iris recognition. However, Mateusz Trokielewicz, M. Szadkow, et.al used both iris and periocular features to identify horses using a convolutional neural network approach. Their goal was to take advantage of the flexibility provided by DCNNs. CNN, especially DCNNs, utilized two-dimensional convolution operations to learn image features at progressively higher-order scales. They collected a new database of images representing horse eyes. They photographed the eyes of 28 horses, including 14 mares, 10 stallions and 4 geldings, and the horses are aged 1 to 24, and its largest group is the Arabian horse [12].

They represented each class with approximately 2000 images. They found it impossible to keep the horse still and not blinking during this time period, so photographs were represented by only eyelids or severely out of focus in the resulting material and were manually checked. These samples were excluded from the final dataset. They refer to the two samples as high-quality and mixed-quality databases, respectively. And the results showed that it was better to train the network on the original dataset. They also found that the horse's two eyes were identified better than the single eye. After proving it through experiments, they found that it is possible to identify horses using DCNNs of eye biomarkers. Although their study would be limited, because of the animal's movement, difficulties arise when trying to quickly acquire images of the horse's eye. But they still see the technology as very promising [12].

According to the investigations, the publication of the paper and the information available online both show that iris recognition is still in the developing stage. However, from the two research that has been mentioned it clearly shows this is one of the areas that could not be neglect, since it always has high accuracy.

5. Conclusion

In the work, we mainly focus on three technologies on animal identification. Facial identification through CNN mimics the processing of the human brain, using the features of animal faces, using algorithms to calculate the distance between eyes and the distribution of the five senses. The recognition accuracy using this technique is generally high. But because the technology relies on cameras and CNN-collected databases, it will be less accurate when applied to wildlife recognition. Iris recognition utilizes the characteristic that each animal has a unique iris with very high accuracy. And using the DCNN technology, iris recognition can learn high-order scale image features, which in turn can characterize fine, texture-related and coarse, more abstract and higher-order inputs, improving the quality of the recognized images. However, since it is difficult to obtain images of horse eyes during the movement of animals, it may reduce the accuracy of iris recognition. Radio frequency identification is a technology that uses radio waves to passively identify tagged objects, usually consisting of consists of a tiny radio transponder, a radio receiver and transmitter. Using ultra-high frequency radio frequency identification, a large amount of data can be stored in the tag and stored in the tag. Offers greater flexibility in terms of reading possibilities, with a wider reading range and faster speeds. However, since the antenna reading range is affected by the surrounding environment, it is likely to be limited in the application environment.

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Undoubtedly, all of the three technologies are worth developing, but still in this stage they all have different degrees of badness and problems. And these are the things that we need to focus on. As all of us are the citizens of this blue planet, as humans, we have the responsibility to help and protect them. This essay employs a self-developed extension of analytical frameworks from relevant literature.

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