Elephant Corridor for movement and Identification Management Using Drone Camera in Deep Neural Networks

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ABSTRACT

Recently, there has been elephant-human conflict is a major problem. Rapid growth in the number death elephant and humans. This trend has resulted in a growing interest in problems requiring solutions. This paper proposes an Elephant Corridor searching model that can extract discriminative features through elephants for individual identification using a drone camera. We present a robust baseline for how individual elephants can be identified using a drone camera. The proposed elephant corridor identification network (CNN Sequential) is a convolutional neural network (CNN)-based Siamese network structure comprising feature extraction and self-attention modules. Moreover, there is no need for a separate scanning device because it uses a popular drone camera pic to acquire the two types of datasets first elephant corridor and the second one is elephant movement. Besides high recognition performance, the proposed method also ensures simplicity and efficiency. The proposed method achieves better recognition performance than state-of-the-art methods for the collected elephant corridor details and elephant movement dataset. Using multiple datasets through cross-validation, we acquired an average identification accuracy of 98.59% with the Rank-1 approach. Additional performance benefits were demonstrated through the receiver operating characteristic (ROC) curve, t-distributed stochastic neighbor embedding (tSNE), and confusion matrix.

KEYWORDS:

Elephant Corridor, identification, Drone Camera, convolutional neural network, residual learning.

I. INTRODUCTION

Elephant corridor and movement has been a promising area of study with drone camera in the fields of computer vision and Deep Learning in recent years. It involves extracting discriminative features by considering Image Processing traits, such as visual appearance, and three dimensional view for, pattern recognition, and elephant corridor and movement (H.S. Kuhl et al., 2013 & S. Kumar et al., 2018). Accordingly, elephant corridor and movement systems have been applied in various areas for elephant corridor, and management, analyses. The harmonious coexistence between people and elephant and the associated responsibility. Therefore, the elephant corridor and movement system is a drone camera for managing and monitoring companion wild animals. The number of incidents associated with elephant corridor and movement can be significantly minimized through drone camera monitoring for elephant conflict and tracking by elephant and reduced the poaching. Moreover, by enabling successful elephant pic as a data, and corridor map is created for data can be collected to overcome the limitations imposed byinsufficient elephant datasets (S. Kumar et al., 2018, 2017).

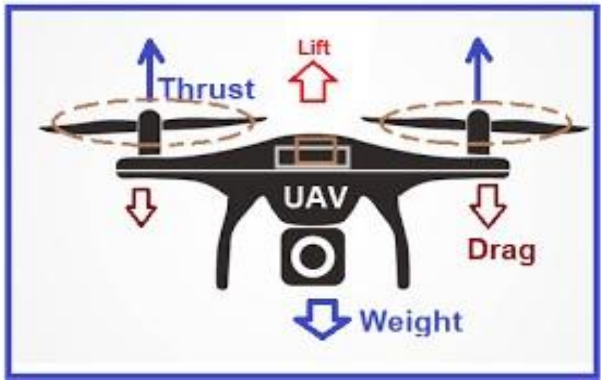

FIGURE 1: show drone camera basic features.

This work focus on the efficiency improvement of forest department for all elephant movement management for drone camera. Methodologies in real-word applications with Chhattisgarh elephant movement. While several sophisticated approaches are met in literature, drone camera use search for elephant corridor and its movements. Today drone camera is not use in for searching, movement for elephant in Chhattisgarh forest. This happens mostly due to the elephant and human conflict that is introduced drone camera monitoring for elephant corridor and the herd movement. step mandatory for our working methods, that can have a great impact on their overall coverage efficiency. A previous work can have a great impact on elephant identification and their identified behavior. But today requirement for minimize human elephant conflict. Our drone work is very impressive and can minimize elephant conflict in Chhattisgarh forest. Fig 1 show the drone basic features. This book chapter introduces to collect the data will be appropriate for 3D Mapping. Chhattisgarh elephant corridor is very big not possible for only human, but our drone camera definitely can minimize the problem of forest department, by analyzing the data and decode the habitat maps.

Fig 2. Drone camera

Now, however, drones are frequently addressing farm level integration of information technology, communication technology, automation and robotics, hunting hurricanes, traffic management, disaster management, forest mapping, forest conservation protecting wildlife and delivering parcels. To contribute the development of an eco-efficient, resource-efficient and competitive agriculture through an enhanced and improved use of Drones and robotics One important new task that drones are currently being assigned to, is mapping. While looking every bit like a basic model airplane that's designed only for recreational purposes but I (Dr Aruna Rana used it in my PhD to collect data of photography by just tying a camera in fuselage withthe help of welcrow and it became an UAV. The light weight drones are now capable of taking thousands of digital images when surveying a landscape. Each one of these images can then be compiled to make a complete and highly accurate 2D and 3D maps.

2. Size and Weight

Other important characteristics of a drone are its size and weight. Distinguishes large drone and small drones, but divided the small drones in multiple subcategories. Drone minimum weight indicators to the drone and 100 kg for multirotor drones. Many countries distinguish Micro and Nano, the Nano drones are less than 250 gms , Micro drones are less than 2 Kg, large and small (or light and heavy) drones. For instance, the Dutch human environment and transport inspectorate makes a distinction between light drone and heavy drone. Light drones are drones lighter than 150 kg and heavy drones are drones of 150 kg or more (Daily mail, 2014). Make a distinction between large and small drones but with different criteria than mentioned above (Custers et al., 2015). The development of drones is currently focused on making smaller and lighter drones for the general public. Large drone is mainly used for military purposes. Therefore, a shift can be observed from large drones to smaller drones. This call for changing the reference categories and the category parameters. Therefore, they suggest to use the term large drone for fixed-wing drones between 20 and 150 and multirotor drones between 25 and 100 kg. Small drones are fixed-wing drones up to 20 kg and multirotor drones up to 25 kg. within the category of small drones, they suggest to use a subcategory of mini drones. Mini drones can vary in weight from several grams up to several kilograms. These mini drones are mainly suitable for indoor applications and recreational applications. Examples of such drone are discussed later in this section.

3. Types of Drones use in Our Work

Multi-rotor Drone

Multi-rotor drones are the easiest and cheapest option for getting an 'eye in the sky' for our major work elephant corridor and movement monitoring. They are also very effective in monitoring purpose and offer greater control over position and framing, and hence they are perfect from forest aerial photography in elephant and surveillance. They are called multi-rotor because they have more than one motor, more commonly tri-copters (3 rotors), quadcopters (4 rotors), hex copters (6 rotors) and octocopters (8 rotors), among others. By far, quadcopters are the most popular multi-rotor drones.

Fixed-wing Drones

A fixed-wing drone has one rigid wing that is designed to suitable for our work. Look and work like an aero plane, providing the lift rather than veridical lift rotors. Hence, this drone type very fast and clear pic the photo and only needs the energy to move forward and not to hold itself in the air. This makes them energy-efficient for long run.

Fig. 3. Fixed-wings drones show by our Aeronautical students MATS university

Single Rotor Drones

Single-rotor drone is strong and durable. They look like similar to actual helicopters in structure and design. A single-rotor has just one rotor, which is like one big spinning wing plus a tail rotor to control direction and stability.

Fig.4. Show the single rotor drone

Fixed-wings Hybrid VTOL

Hybrid VTOL drone types merge the benefits of fixed-wing and rotor-based designs. This drone type has rotors attached to the fixed wings, allowing it to hover and take off and land verifiably. This new category of hybrids is only a few on the market, but as technology advances, this option can be much more popular in the coming years. One example of fixed-wing hybrid VTOL is Amazon's Prime Air delivery drone.

Fig. 5. Fixed-Wings Hybrid VTOL drones show for our university students

Broad Casting Drones

The use of drones provides broadcasters with an innovative way of capturing events, the small and light-weight nature of the technology allows the media to get footage of the action like never before. ESPN trialed drones at the X Games in early 2015, as fox used them indoors at the aim super cross series in march and again during golf's U.S. open. Both broadcast and camera technologies get smaller and lighter, the shooting platform also becomes more compact. What once required a chopper can now fit in small and drones. So how can new technologies like 5G and 8K video transform live broadcasts.

Fig. 6. Show the Broad Casting Drones

4. Related Work

Out of the numerous grid-based CPP works, in this section, we have selected to present some of the most interesting, relatively recent ones. The works are presented in ascending chronological order and some of the advantages and disadvantages of each work are highlighted. The authors in (14) propose an offline flight planner for a quad-rotor UAV that calculates coverage trajectories to ensure qualitative data gathering for image mosaicking. The presented solution segments the workspace using approximate cellular decomposition, with the size of each cell determined by the UAV's sensor reading and the desired overlap between two sequential images, to facilitate post-processing of the data for image mosaicking. In (15) a grid-based methodology for multi-robot coverage path planning (MCPP) is presented. The key idea in this work is that the multi-robot problem can be solved efficiently by dividing the overall ROI to exclusive sub-regions, equal to the number of robots that will be utilized for the coverage procedure, and then solve a typical CPP problem for each sub-region. For this work the "Divide areas Algorithm for Optimal Multi-Robot Coverage Path Planning" (DARP) algorithm is introduced to undertake the area allocation procedure. The spanning tree Coverage (16) (STC) algorithm is applied to all sub-regions to generate the coverage paths inside them. The methodology presented in the paper offers a simple, efficient and safe solution to the multi-robot problem, eliminating the possibility of intersecting trajectories, that can contribute to the development of more efficient and effective MCPP solutions for various applications.

5. PROPOSED SYSTEM

The proposed system for elephant corridor and movement monitoring for Chhattisgarh forest two main components. The first one is the drone searching all corridors and second one is the monitoring elephant movement. This two component is very useful to reduce the elephant conflict the identification of the individual elephant's. The overall system flow of the proposed system.

Automatic Detecting in Drone Camera

Elephant's elephant corridor and movement monitoring for Chhattisgarh forest the process flow of automatic detection and cropping of the images. For detecting the elephant firstly, we perform the inter-frame differencing between two consecutive frames of the elephant's and corridor field image in order to detect the elephant. Then we transform the inter-frame differencing result into the binary image by using the predefined threshold. The equation of inter-frame differencing method-based binary image creation is described in equation (1). 1 if threshold, 0 otherwise

$$Mt(x) = \begin{cases} 1, if \ |It(x) - \ It - 1(x)| \ \geq Threshold \\ 0, \quad otherwise \end{cases} \qquad (1)$$

Where

$M_t(x)$ is the result binary image of frame t,

$I_t(x)$ is the elephant's image and corridor images at frame t and

$I_t - 1(x)$ is at the previous (t-1) frame

Then, we use the white pixel occurrences (350 pixels) as a Threshold in order to find the elephant corridor and movement monitoring. If the horizontal histogram count is greater and less Threshold, we regard that elephant corridor location as pole location. If elephant image and elephant corridor are two poles' locations are detected, we use the corridor location which is located near the previous detected pole. For image cropping, we use the copping height and width by the fixed value of 450 pixels and 850 pixels, respectively because the distance between two poles location and the length of the pole are the same for all frames. After getting the pole location, we check it for finding the cropped image direction. If the value of y coordinate of detected pole plus the image cropped height threshold of 450 is less than or equal to the height of the original corridor or elephant image, then cropping is performed over the lower 450 pixels' area of the elephant's corridor and elephant image, otherwise, the upper 450 pixels' area is cropped. Count the frequency of the occurrence of image pixels in the horizontal direction of each point along the vertical axis. As a result, we got the horizontal histogram of the binary image. The size of each frame is 1024×768.

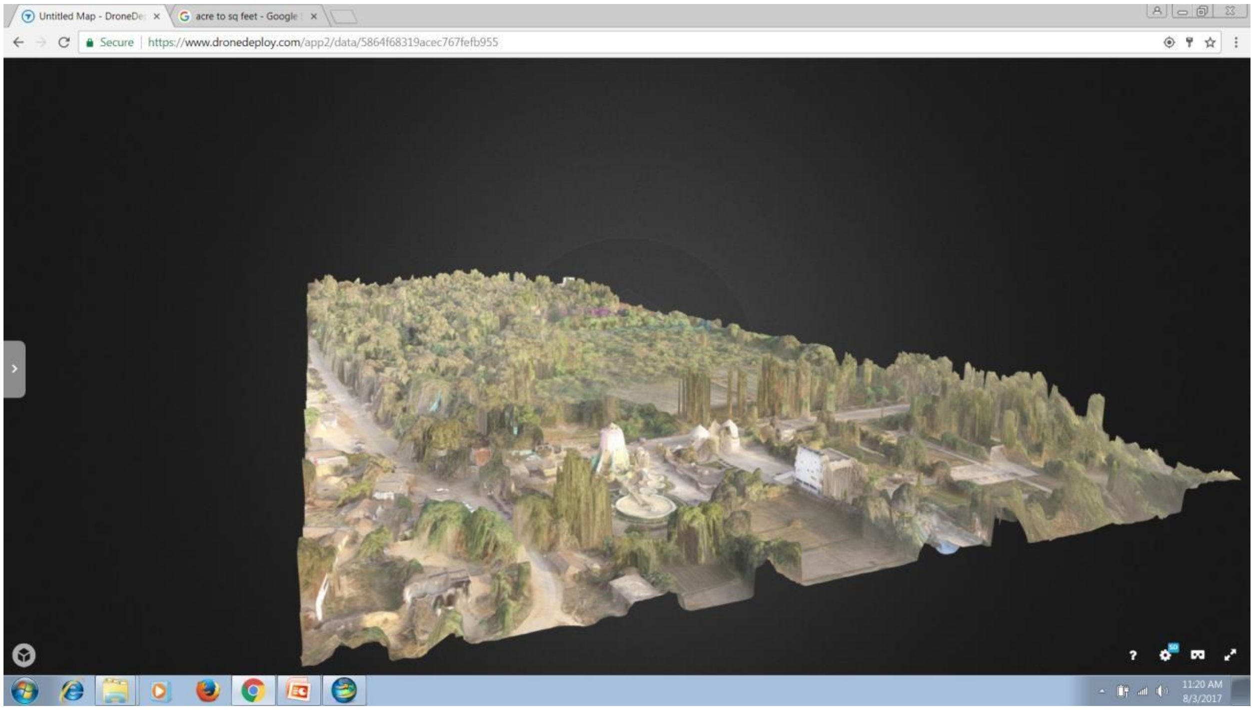

Fig.7 3D map of forest

The original feature maps obtained through the first step are then concatenated with the channel axis for each map obtained through the reshape images and channel attention module in the second step. The final embedding vector is attention model obtained through a fully connected (FC) layer. We used contrastive loss (R. Headsell et al., 2006) to optimize our model. The contrastive loss is calculated by checking and applying the binary label to a pair of positive-negative elephant image and corridor image inputs. We also added additional margin-based loss (J Deng et al., 2019) to extract the discriminative embedding vectors of the CNN model. The loss is considered with the contrastive loss to optimize CNN model. The experimental outcomes indicate that the proposed CNN model framework illustrates superior recognition performance to state-of-theart methods for the collected elephant images dataset. The contributions of our proposed CNN model framework are as follows: • The proposed CNN model method improves individual elephant corridor and elephant movement managing systems' performance through elephant based on deep learning techniques. Our method is the first attempt to identify an individual elephant based on deep learning models. We provide a robust baseline model through the CNN model method for individual elephant identification systems. • We ensure stable and discriminative feature extraction by integrating the CNN model modules into end-to-end training and combined objective functions to optimize the CNN network. • We experimentally demonstrate the superior performance for our collected elephant dataset compared to state-of-the-art methods. We acquired an average elephant identification and elephant corridor map creating accuracy of 98.59% with the Rank-1 approach.

DEEP LEARNING FEATURE-BASED METHODS

Recently, deep learning for animal identification has become a key area of development in computer vision technology. Deep-learning approaches are popular for the image recognition, image classification, image detection, and image tracking of objects for drone camera. Therefore, elephant images and elephant corridor image identification recognition through deep learning. The CNN is a popular for image identification by CNN deep-learning architecture that has demonstrated outstanding performance in various image computer vision tasks (B. Shameem et al., 2021, K. He et al., 2016, Krizhevsky et al., 2012). (Hansen et al., 2018) proposed an animal identification system of individual images that uses a CNN model for training and testing with an artificially augmented dataset from an unconstrained commercial farm environment. (Deb et al., 2018) presented an animal face recognition system called PrimNet, where mobile applications were used to directly obtain camera images of three primates in the wild: lemurs, golden monkeys, and chimpanzees. (Hou et al., 2020) used CNN with deep learning to propose a new individual identification system for the giant panda; they ensured the effectiveness and reliability of the panda image identification model by considering multiple treatments under various conditions, such as panda large face angle, low brightness, and high saturation. (Wang et al., 2019) used a CNN with residual learning to study the unique panda facial features for gender classification. (Kumar et al., 2018) proposed an approach using individual deep-learning architectures, such as a CNN and a deep belief network (DBN), for individual cattle identification. The performance of muzzle print approach was superior to that of the handcrafted featurebased approach that was previously applied using muzzle print images. (Favorskaya and Pakhirka, 2019) presented animal identification in the wildlife based on muzzle and shape features using a joint (CNN. Hu et al., 2020) proposed a elephant-identification system based on the deep parts features; they use side-view images of the elephant and corridor images, to identify individual images.

Fig. 8. Sample images of 13 elephants' images

6. EXPERIMENTS

DATASETS

In this study, we use the elephant and forest some picture images to identify elephant and corridor. The elephant only can be used as an identifiable means of biometric authentication, such as human iris pattern, and fingerprints. These elephant and corridor also have the advantage of not changing over time. Therefore, elephant images are used to enable identification regardless of elephant images. However, because it is difficult to find or obtain elephant images datasets for the elephant images dataset, the dataset is obtained directly. Several Elephant rehabilitation and rescue center were visited to collect elephant images dataset. Each elephant was identified with its name. Therefore, there are no duplicated IDs in the elephant dataset. The dataset images were collected outside under sunlight or inside under Shad. The elephant images dataset was collected using mobile phones without extra scanning equipment. This dramatically increases the convenience and efficiency of Elephant images data collection and processing using mobile devices. The images were taken with a resolution of 5,032 pixels in the horizontal direction and 4,024 pixels in the vertical direction, and the elephant images areas were cropped automatically. Only those elephant images with more than 640 pixels were selected for inclusion in the elephant images dataset. Finally, 2,561 elephant images from 13 elephants were collected for the dataset.

EXPERIMENTAL SETUP

IMPLEMENTATION DETAILS

In experiments, our networks were implemented using Python (B. Shameem et al., 2022). The experiments were conducted on a laptop computer with an Intel(R) Core(TM) i5 CPU @ 3.20 GHz and 16.0 GB RAM. Before performing the image classification with the (CNN Sequential Module) proposed method, the collected elephant body part images dataset input elephant images were resized to predict

TABLE 1: Confusion matrix scheme.

Predict			
		Positive	Negative
Actual	Positive	TP(True Positive)	FN(False Negative)
	Negative	FP(False Positive)	TN(True Negative)

Positive Negative Actual Positive TP (True Positive) FN (False Negative) Negative FP (False Positive) TN (True Negative) 256 × 256 pixels. The batch size used was 13, and the network was trained for 23 epochs. Two objectives were simultaneously considered to optimize the network in an end-to-end manner. The fixed hyper parameter of contrastive loss was m = 2,. To optimize the proposed, the CNN Sequential, we used the Adam (B. Shameem et al., 2021) optimizer with β1 = 0.5 and β2 = 0.999. Furthermore, the hyper parameters s and m for loss were set to 30 and 0.5, respectively. We optimized the network module responsible for using the stochastic gradient descent (SGD) method, where the momentum was 0.9 and weight decay was 0.0005. The initial learning rate was 0.0001, which was maintained over the first 100 epochs and linearly decayed to zero over the next 100 epochs. The embedding vector size used for the feature matching was set to 1,024-dimensions.

EVALUATION METHODS

We study and comparisons with other state-of-the-art methods. Furthermore, we present all experimental results through the five-fold cross-validation, a CNN Sequential method that can be considered at this time because it is so difficult elephant corridor and elephant image collection to determine the generalization performance of the CNN Sequential model only with validation results when there are insufficient elephant corridor and elephant images datasets. The basis of model performance evaluation follows the confusion matrix shown in Table 1. The accuracy of elephant identification is achieved through feature matching of the acquired embedded vectors for the testing set. The model performance was also evaluated by the receiver operating characteristic (ROC) curve and the model verification rate of the specific false acceptance rate (FAR). Furthermore, the confusion matrix and the distributed stochastic neighbor embedding (D-SNE) algorithm was used for performance evaluation.

Accuracy = T P + T N T P + F N + F P + T N -------------- (2)

F AR = F P F P + T N. ....(3)

F RR = F N T P + F N. ....(4)

T AR = 1 − F RR = T P T P + F N---------------------------- (5)

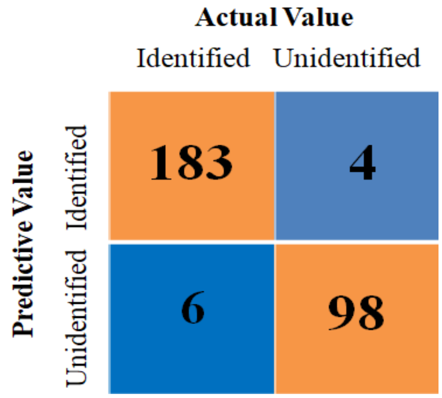

Fig. 9. Confusion matrix using the validation set for

CONCLUSION

This paper proposes an Elephant corridor and elephant movement identified (CNN model) deep-learning framework for individual of Elephant images. Our method is the first attempt to identify an elephant images patterns based on deep learning models. The CNN model method aims to obtain robust and discriminative features that can extract the unique patterns in an elephant images. As ablation studies demonstrate, the performance of combining objective functions for CNN network optimization with integrated modules that constitute CNN model is more stable than using only part of the CNN model enables more stable and discriminative feature extraction to identify features using the elephant body part images. Moreover, our experiments demonstrate that our proposed approach outperforms state-of-the-art CNN methods on the collected elephant images dataset. Consequently, the proposed CNN model method can serve as a robust baseline for individual elephant identification. In future work, we will discuss improvements in elephant identification and elephant corridor monitoring by drone camera systems by extending the elephant images dataset. We also plan to obtain an elephant images dataset for additional wild animals, such as tiger leopard etc. As previously noted in related studies, elephant images are important feature extractions that distinguish wild species characteristics. Therefore, we will apply it to the task of identifying elephant. Elephant's image and corridor movement identification using the rehabilitation differencing and horizontal histogram-based method for automatically detecting and cropping of elephant's and corridor map for training and recognition of the elephant's image. We also create the elephant's image dataset of 13 different elephant images and perform the experiments on that dataset. The proposed system got an accuracy of 96.8% for automatically detecting and cropping an elephant's and corridor map region and 97.01% for elephant identification.

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Z. Dr Aruna Rana PhD Thesis 2006 guided by Major Dr AK Dwivedi (Retired Principal Higher Education Department Madhya Pradesh) and co-guided by Dr Girish Kant Pandey (Professor and HoD Defence Studies Department, Govt Nagarjuna PG Science College, Raipur, on topic of “TACTICAL EMPLOYMENT OF RADIO CONTROL MODEL FLYING SYSTEM (RCMF)”