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Proposed System for Efficient Wildlife Monitoring Using WSN and Image Processing *

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1 Introduction

The ecological cycle is affected by several factors in our environment. For instance, the Eurasian teal and the white-fronted goose distress wetlands ecosystems, leading to drought and a lack of wet climate. These factors are considered the main reason for the climatic change, obviously, a factor from several factors that have a considerable impact on this phenomenon. To counter this situation, researchers monitor species of birds having an influence on ecosystems in order to predict critical situations and propose solutions that deal with these warnings. However, the monitoring process constitutes a huge burden load on the responsibility of monitoring agents due to the complex tasks of counting these species in the correct manner. For this reason, several research aims at reducing these tasks using new technologies of auto-counting, especially with the apparition of AI solutions^[6]. Nowadays, AI solutions are involved in several domains. These solutions are able to replace human intervention. Nevertheless, their correctness relies on the modeling process of these schemes. Hence, the choice of an adequate method is a crucial decision to resolve a certain issue. We believe that the counting tasks constitute a huge responsibility of the monitoring agent, given the fact that this issue can be countered using smart schemes, based on AI methods [6]. To overcome this situation, the paper put forwards a scheme, based on WSN, on which sensors are equipped with cameras, and transmits sensed images toward the edge. After that, the edge processes and extracts information from sensed images to count the number of species in a surveillance region. To achieve this goal, the edge inputs detected images to a conventional neural network (CNN), on which its output is the number of recognized birds. But the counting given by CNN is still incomplete, because the counting may be wrong due to the intersection of the region of interest detected by cameras. Our proposal deals with this problem by using feature extraction and matching algorithms to detect the common region of interest and eliminate redundant counting. The validation of our scheme has been conducted by studying the offered feature extraction and matching algorithms and analyzing their performances under networking factors (i.e., latency, packet loss, etc).

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2 Proposed system

WSNs are self-contained systems that consist of small sensors with built-in sensing units, a general-purpose computing unit, and limited transmission capabilities [7]. The proposed architecture consists of multiple groups of sensing nodes (SN), led by a cluster head (CH) responsible for collecting and compressing data from shared sensor nodes within the group before transmitting the processed data to the base station (BS) [7]. The assigned tasks are based on their complexity and their availability on certain levels illustrated in FIG. 1.

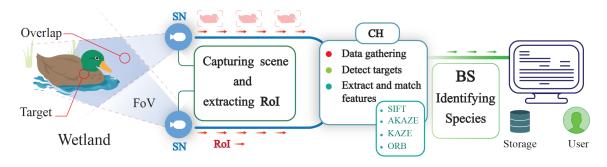


FIG. 1: System deployment .

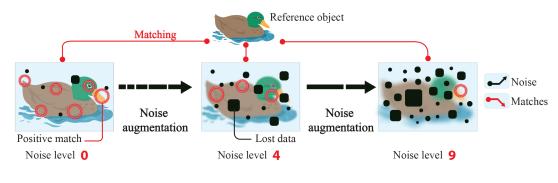
2.1 RoI and feature extraction robustness (Data loss)

The use of RoI^1 detection techniques [3] in a video sequence containing continuous target occurrence can reduce the amount of transmitted data by up to 80% compared to transmitting raw, unprocessed data. This was demonstrated through experiments involving transmitting data with and without RoI detection. Results are shown in FIG. 4. The present experiment proposes an implementation for evaluating the noise robustness of various FD². The experiment involves simulating different levels of noise and data loss in a set of reference images and comparing them to their corrupted counterparts. FD SIFT [4], KAZE [2], AKAZE [1] and ORB [5] which are known for their effectiveness in detecting and extracting features from images, are employed along with feature matchers, selected for their ability to match features across images. The implementation employs functions to generate images with different noise levels, detect and compute key points and descriptors from images, and match features between a reference image and the generated noisy images. Positive matches, those that correspond to the same object or scene in both images (the noisy and the reference) are filtered based on a matching criterion as in [4]. Noise levels refer to the degree of distortion introduced in the image due to random factors such as transmission or data loss, we add black boxes to the input image at random locations, gradually increasing their size, while also adding Gaussian noise. By increasing the size of the black boxes and the Gaussian noise, the degree of data loss increases, which simulates real-world scenarios where data is missing due to poor transmission or corruption. To evaluate the noise robustness of the FD and matches the experiment shown in FIG. 2. The utilization of various techniques is essential in order to determine the most efficient and effective approach for our specific application, ultimately enabling us to make an informed decision that aligns with our goals and objectives. The resulting FIG. 3 shows a decrease in the amount of positive valid matches when the noise levels are augmented this is due to Feature detection algorithms relying on the presence of specific patterns in the image to identify and extract features and can be sensitive to data loss from images caused by lighting, perspective, and other environmental factors. This can make it difficult for the algorithm to detect features accurately. However, KAZE is a better choice for lossless networks, while SIFT's ability to tolerate errors and maintain accuracy in the presence of distortions makes it better for WSN. Selecting a threshold value for recognizing the bird count using SIFT/KAZE feature matching can be difficult due to variability in factors such as image quality, bird size,

¹RoI: Region of Interest

²FD: Feature Detectors

data loss and balancing the number of correct matches against the number of false matches is crucial in determining the optimal threshold value to accurately recognize the target object. To address the fragility and accurately detect the number of birds present in an image, the development of an AI model is necessary.



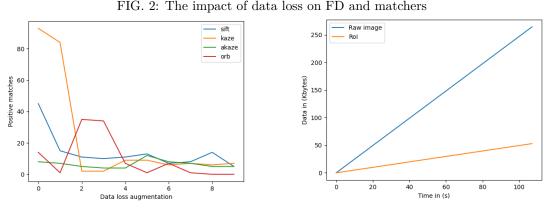


FIG. 3: Positive matches over data loss levels.

FIG. 4: Transmitted data (RoI and Raw).

3 Conclusion

The use of RoI can prove beneficial in reducing networking costs, thereby extending the lifespan of sensing nodes. Propagation of such errors 2.1 can significantly impact subsequent network layers, resulting in a cascading effect that undermines network performance such as species identification. The deployment of an appropriate Machine Learning (ML) model capable of handling the fragility of the FDA is necessary.

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