PAPER • OPEN ACCESS

Computer vision-based techniques for cow object recognition

Computer vision-based techniques for cow object recognition

R W Bello[1, 2, 5], A S A Mohamed[1], A Z Talib[1], D A Olubummo[3], and O C Enuma[4]

[1] School of Computer Sciences, Universiti Sains Malaysia, 11800, Pulau Pinang, Malaysia

[2] Department of Mathematics/Computer Science, University of Africa, Toru-Orua, Bayelsa, Nigeria

[3] Department of Computer & Information Systems, Robert Morris University, Moon-Township, Pennsylvania, United States of America

[4] Department of Planning, Research and Statistics, Ministry of Health, Bayelsa State, Nigeria

[5] E-mail: sirbrw@yahoo.com

Abstract. The productivity of livestock farming depends on the welfare of the livestock. This can be achieved by physically and constantly monitoring their behaviors and activities by human experts. However, the degree of having high accuracy and consistency with manual monitoring in a commercial farm is herculean, and in most cases impractical. Hence, there is a need for a method that can overcome the challenges. Proposed in this paper, therefore, is the cow detection and monitoring method using computer vision techniques. The proposed method is capable of tracking and identifying cow objects in video experiments, thereby actualizing precision livestock farming. The method generates reasonable results when compared to other methods.

1. Introduction

Livestock monitoring is a herculean task especially when it involves physical and manual monitoring of their welfare in a commercial farm [1]. Human experts are mostly trained to diagnose and detect the welfare challenges of livestock using their physical appearance [2]. However, the limitations in labor and time prevent the human experts from having high accuracy and consistency in the monitoring of the livestock [3]. Consequently, there is a rising demand for substituting computer vision techniques for human experts [4]. Without a doubt, the application of techniques involving video analytics has cut across different domains including animal husbandry, and this is made possible through series of vision and image processing algorithms making animal biometrics an emerging research area among researchers [5]. The feasibility of developing a system for detecting and locating individual cow objects can be made possible using computer vision techniques [6]. In performing the tasks involved in this paper, the particle filter (PF) algorithm [7] was enhanced (PF_{tm}) and combined with mean-shift [8] (MPF_{tm}). While PF_{tm} involves the incorporation of temporary memory (tm) to store the former location of the cow and predict the next likely location using the former location that was stored, MPF_{tm} on the other hand adds to the tracking accuracy using its capable algorithm to detect and provide necessary information about the movement sensitivity of the object.

2. Related works

Recently, research in visual object monitoring has greatly been accepted by the community of computer vision. Monitoring visual objects is still a difficult task to accomplish despite the discovery that has led to the development and implementation of several visual object algorithms for object monitoring. Variation in illumination, instability in object posture, and similarity in color of objects and their environment are several factors that could affect the successful implementation of object tracking and monitoring. Zhang et al. [9] categorized the methods employ in monitoring visual objects into probabilistic methods and deterministic methods where mean-shift is frequently used as one of the deterministic methods [10, 11]. In this paper, mean-shift, and the algorithms of particle filter and Kalman filter were studied for individual cow tracking and detection. This is to enable the possibility of health and performance monitoring of individual cows, especially when in the ranch or on an official test [12].

2.1. Mean-shift

Mean-shift, for its robustness against partial occlusion, is the most widely accepted and employed method for virtual object tracking and monitoring from among the several deterministic methods. Moreover, being effective during computation without wasting time, effort or expense makes the mean-shift algorithm suitable for implementing real-time tracking and monitoring of objects. However, the possibility of tracking full occluded and fast-moving objects with mean-shift is minimal.

2.2. Kalman filter algorithm

To the highest degree, the Kalman filter [13, 14] represents one of the probabilistic methods applied in visual object tracking. The development and implementation of the Kalman filter using a robust algorithm enable easy prediction of the location of any linearly moving and occluded object during tracking task in a real-time scenario, making the method appropriate for linear system estimation [15]. Nonetheless, the application of the Kalman filter is not a perfect method when it involves the tracking of a non-linear moving object. The non-linear movement [16] of target objects in real-life scenarios due to changes in their trajectory is the major reason for the inability of the Kalman filter in tracking a non-linear moving object.

2.3. Particle filter algorithm

Unlike the Kalman filter, the particle filter algorithm [17, 18] is an effective and efficient probabilistic method of visual object tracking that can handle problems involving objects' non-linear movement [19]. However, its application is not appropriate for visual object tracking in a real-time environment because of the following: (1) it reduces tracking performance, (2) it involves massive computation, and (3) it involves a huge amount of particles as samples.

3. Materials and methods

The breed of cow employed in performing the experiment in this study is Muturu. Three analytic experiments were performed on the cow video dataset (50 frames) using both existing and proposed methods. Figure 1 shows the flowchart of the enhanced object tracking method. The cow activity as analyzed at t-2 (Figure 2) predicts the next possible location of the cow. Three time-frames at t, t-1, and t-2 were initialized. The coordinates were randomly assigned throughout the first three steps. The identification of the cow coordinates enables the estimation of the next movement and this is by allocating a higher weight to the cow at the upper right quadrant. By this, if the value of x at time t and t-1 shows any similarity, consideration for recalculation is given to the coordinate of t-2 for identification of the next potential location of the cow as shown in Figure 2.
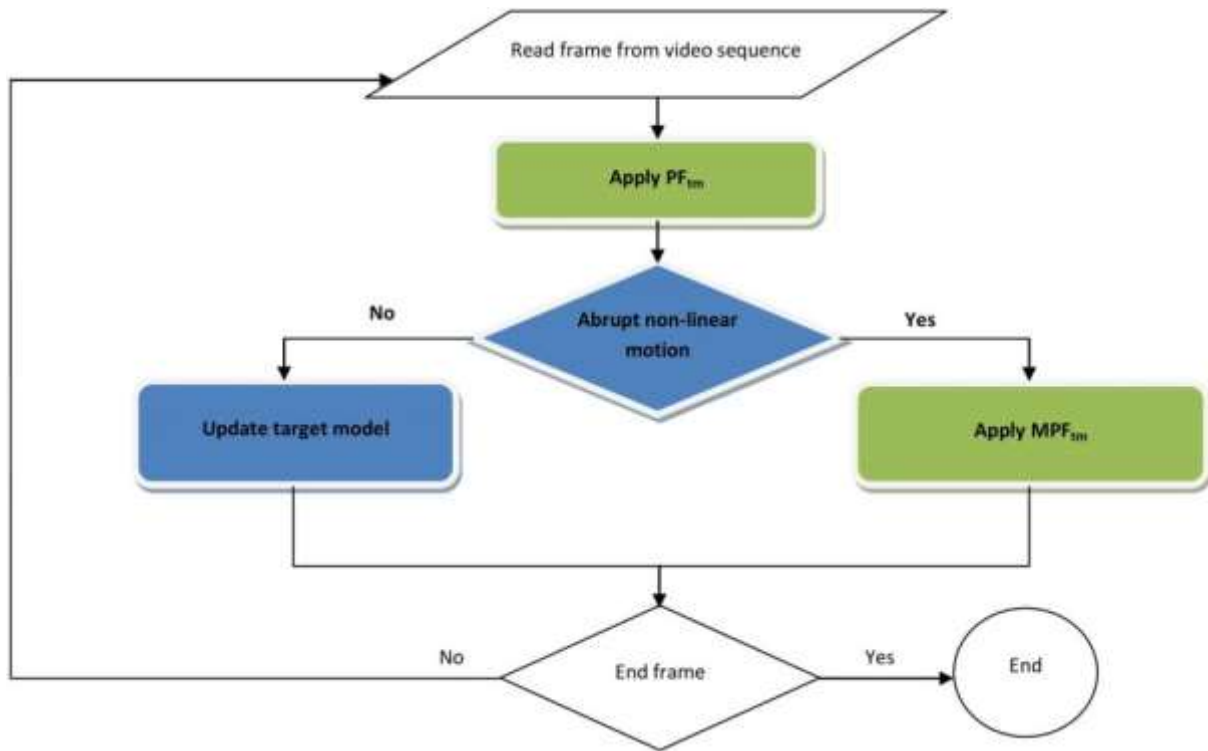
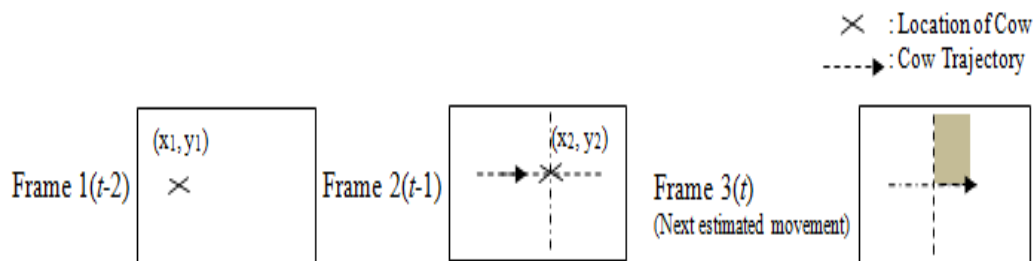**Figure 1.** Flowchart of the enhanced object tracking method.

Figure 2. The possible scenario of cow movement.

The precision-recall method is employed and calculated for the tracking and detection of individual cow objects. The formula for defining precision (P) is as follows:

$$P= TP/TP+FP \qquad (1)$$

And the formula for defining recall (R) is as follows:

$$R= TP/TP+FN \qquad (2)$$

A true positive (TP) is an outcome where the model correctly predicts the positive class. A false positive (FP) is an outcome where the model incorrectly predicts the positive class and a false negative (FN) is an outcome where the model incorrectly predicts the negative class.

4. Implementation

MATLAB R2019b was installed on a Microsoft Windows 10 with Microsoft Visual Studio 2019 as the integrated development environment (IDE) to implement the analytic experiments. Figure 3a and Figure

4a show the cow real-time tracking system. While Figure 3a and Figure 3b respectively show the tracked cow objects undergoing particle filtering, and the pseudocode to detect the cow objects, Figure 4a and Figure 4b respectively show the tracked cow objects with their bounding boxes, and the pseudocode of detection to track assignment.
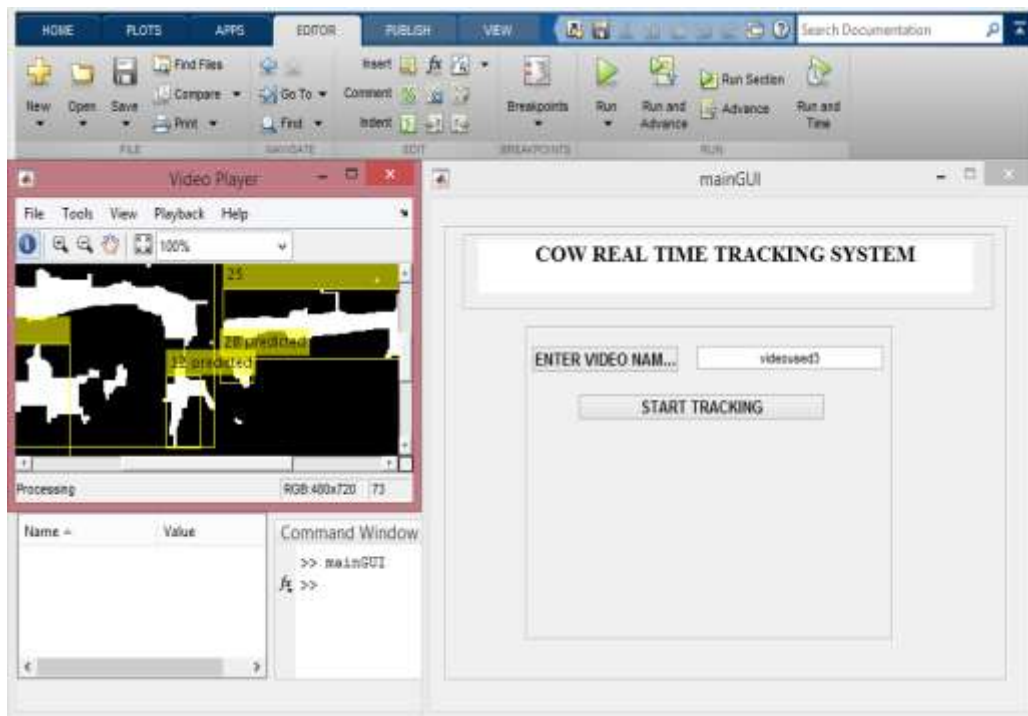

Figure 3a. Tracked cow objects undergoing particle filtering.

Pseudocode to Detect Objects

```
function [centroids, bboxes, mask] = detectObjects(frame)
global obj
      % Detect foreground.
      mask = obj.detector.step(frame);

      % Apply morphological operations to remove noise and fill in holes.
      mask = imopen(mask, strel('rectangle', [3,3]));
      mask = imclose(mask, strel('rectangle', [15, 15]));
      mask = imfill(mask, 'holes');

      % Perform blob analysis to find connected components.
      [~, centroids, bboxes] = obj.blobAnalyser.step(mask);
   End
```

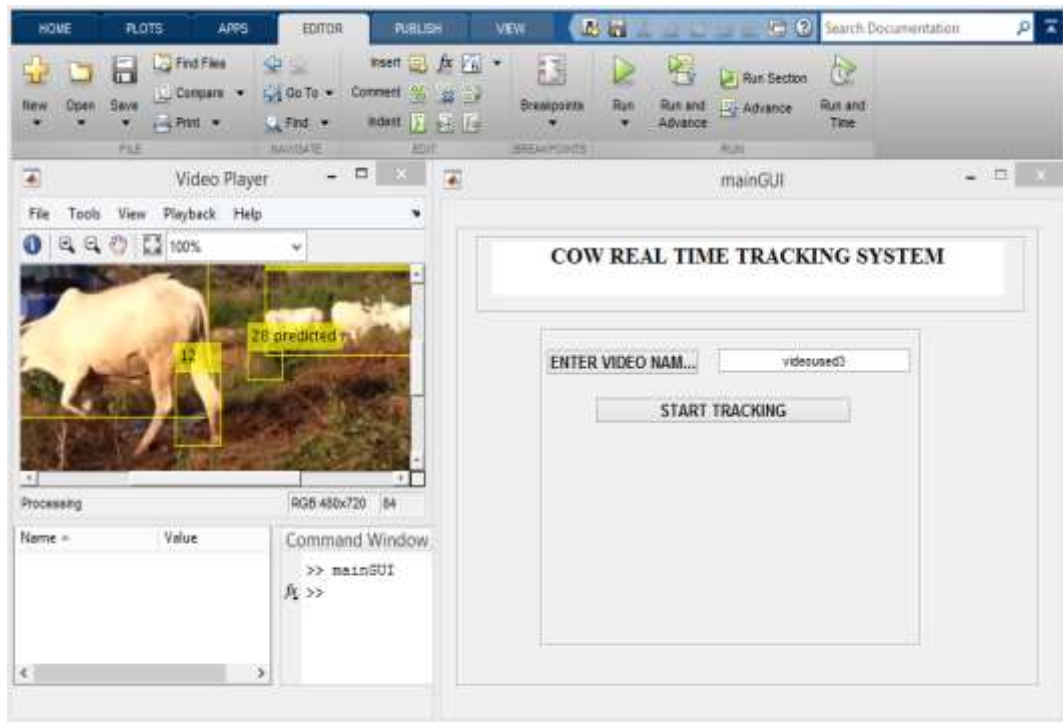**Figure 3b.** Pseudocode to Detect Objects.

Figure 4a. Tracked cows with their bounding boxes and predictions.

Detection to Track Assignment

```
function [assignments, unassignedTracks, unassignedDetections] = ...
    detectionToTrackAssignment()
global obj tracks centroids
    nTracks = length(tracks);
    nDetections = size(centroids, 1);

    % Compute the cost of assigning each detection to each track.
    cost = zeros(nTracks, nDetections);
    for i = 1:nTracks
        cost(i, :) = distance(tracks(i).kalmanFilter, centroids);
    end

    % Solve the assignment problem.
    costOfNonAssignment = 20;
    [assignments, unassignedTracks, unassignedDetections] = ...
        assignDetectionsToTracks(cost, costOfNonAssignment);
end
```

Figure 4b. Pseudocode of Detection to Track Assignment.

5. Results and discussion

Figures 4-6 show the cow's real-time tracking results. Figure 5 shows the qualitative comparison between the tracking results for non-linear motion of cow objects using PF and PF_{tm}. PF_{tm} shows improvement over the PF method in tracking the cow non-linear motion. Figure 6 shows the qualitative comparison between the tracking results for partial occlusion of cow objects using MPF and MPF_{tm}. MPF_{tm} shows improvement over the MPF method in tracking the partial occlusion. Figure 7 shows the

qualitative comparison between the tracking results for full occlusion of cow objects using MPF and MPF$_{tm}$. MPF$_{tm}$ shows substantial improvement over the MPF method in tracking full occlusion. The tm (temporary memory) is employed to predict the target object position using previously stored position especially when the results recorded for particle filter and mean-shift tracker are not convincing due to high concentration of particle distribution in them. Figure 8 shows tracking results based on center errors. The center errors for PF$_{tm}$ (dotted blue line) and MPF$_{tm}$ (red line) are less than the center errors for PF (dotted green slant line). These results imply that the particle filter algorithm has been successfully enhanced in PF$_{tm}$ and MPF$_{tm}$ as proposed methods for accomplishing the tracking task.
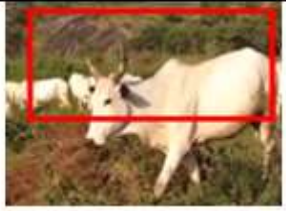

Figure 5. Tracking results for non-linear motion.

Figure 6. Tracking results for partial occlusion.

Figure 7. Tracking results for full occlusion.
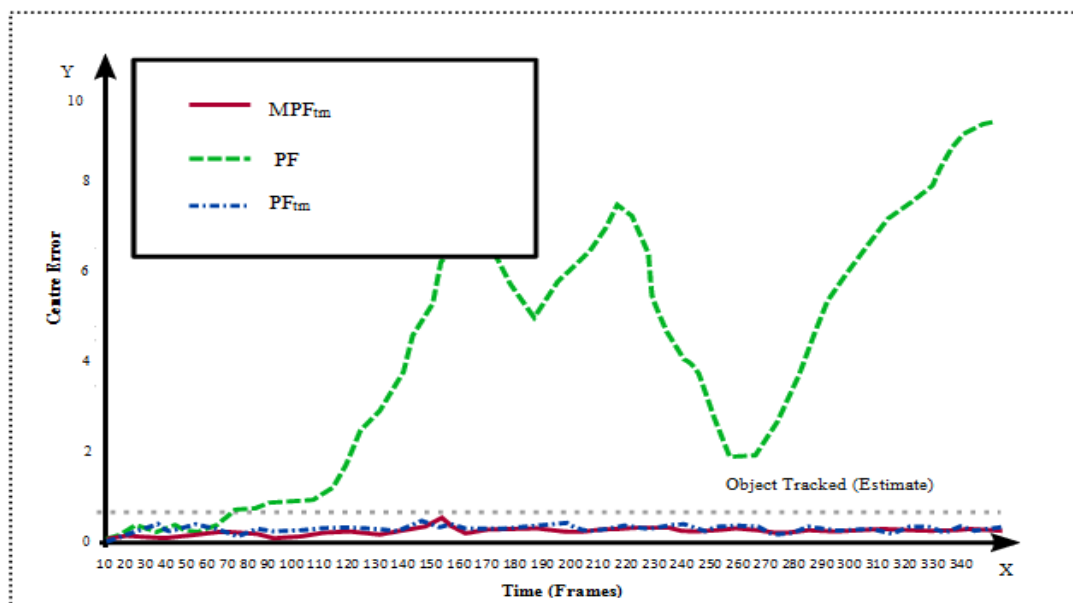
Figure 8. Tracking results based on center error.

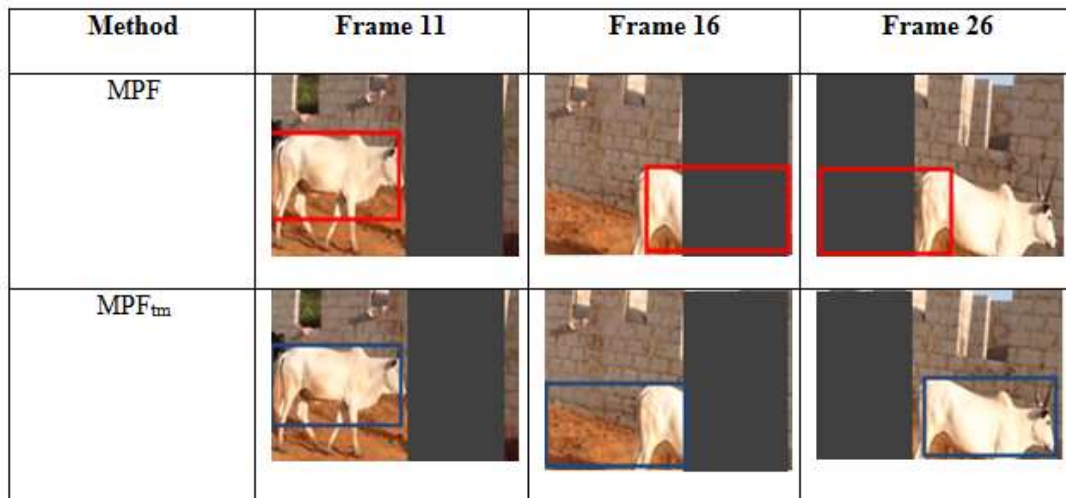Table 1 shows the quantitative results of cow detection using the precision-recall method. MPF_{tm} achieved 89% precision and 85% recall more than PF_{tm} and PF, which achieved 85% precision and 82% recall, and 82% precision and 80% recall respectively. This result implies that both MPF_{tm} and PF_{tm} as proposed methods have higher detection accuracy more than the particle filter (PF) algorithm.

Table 1. Cow detection results using the precision-recall method.

Method	Category	True detection (true positive)	False detection (false positive)	Precision (%)	Recall (%)
PF	Tracked	79	17	82	80
	Mistracked (false negative)	20	-		
PF_{tm}	Tracked	88	15	85	82
	Mistracked (false negative)	19	-		
MPF_{tm}	Tracked	99	12	89	85
	Mistracked (false negative)	18	-		

6. Conclusion

Tracking and detection of cow objects in video experiments have been presented in this paper. The experiment was performed by enhancing the particle filter algorithm (PF_{tm}) and combining it with the mean-shift tracker (MPF_{tm}). While PF_{tm} involves the incorporation of temporary memory (tm) to store the former location of the cow and predict the next likely location using the former location that was stored, MPF_{tm} on the other hand adds to the tracking accuracy using its capable algorithm to detect and provide necessary information about the movement sensitivity of the object. The MPF_{tm} and PF_{tm} showed fewer center errors than PF, and they also recorded precision accuracy of 89% and 85% respectively higher than PF that recorded 82% accuracy. Our future work includes segmentation of the detected cow objects for individual classification.

References

[1] Sharma B and Koundal D 2018 Cattle health monitoring system using wireless sensor network: A survey from innovation perspective *IET Wireless Sensor Syst.* **8**(4) 143-51

[2] Halachmi I, Guarino M, Bewley J and Pastell M 2019 Smart animal agriculture: Application of real-time sensors to improve animal well-being and production *Annual Review Animal Biosci.* **7** 403-25

[3] Chen C S and Chen W C 2019 Research and development of automatic monitoring system for livestock farms *Appl. Sci.* **9**(6) 1-16

[4] Muller M, Bibi A, Giancola S, Alsubaihi S and Ghanem B 2018 Trackingnet: A large-scale dataset and benchmark for object tracking in the wild *In Proceedings of the European Conference on Computer Vision* pp 300-17

[5] Bello R W, Talib A Z H and Mohamed A S A B 2021 Deep belief network approach for recognition of cow using cow nose image pattern *Walailak J. Sci. Technol.* **18**(5) 1-14

[6] Bello R W, Talib A Z and Mohamed A S A 2020 Deep learning-based architectures for recognition of cow using cow nose image pattern *Gazi Univer. J. Sci.* **33**(3) 831-44

[7] Qiao N and Yu J X 2014 On particle filter and mean shift tracking algorithm based on multi-feature fusion *In Proceedings of the 33rd Chinese Control Conference* IEEE pp 4712-5

[8] Hou Z Q, Liu X, Yu W S, Li W and Huang A Q 2014 Mean-shift tracking algorithm with improved background-weighted histogram *In 2014 Fifth Intern. Conf. Intell. Syst. Design Engin. Appl.* pp 597-602

[9] Zhang J, Sun H, Guan W, Wang J, Xie Y and Shang B 2010 Robust human tracking algorithm applied for occlusion handling *In 2010 Fifth Intern. Conf. Front. Comp. Sci. Technol.* pp 546-51

[10] Ju M Y, Ouyang C S and.Chang H S 2010 Mean shift tracking using fuzzy color histogram *In 2010 International Conf. Machine Learning and Cybernetics* IEEE pp 2904-08

[11] Bello R W, Mohamed A S A and Talib A Z 2021 Real-time cow detection and identification using enhanced particle filter *In IOP Conf. Series: Materials Sci. Engin.* IOP Publishing **1051**(1) pp 1-8

[12] Bello R W, Olubummo D A, Seiyaboh Z, Enuma O C, Talib A Z and Mohamed A S A 2020 Cattle identification: the history of nose prints approach in brief *In IOP Conf. Series: Earth . Environ. Sci.* IOP Publishing **594**(1) pp 1-9

[13] Yang Y X, Gao Y and Zhang X Y 2010 Visual tracking for soccer robot based on adaptive kalman filter *In 2010 Second Pacific-Asia Conf. Circuits, Commun. Syst.* **2** pp 27-30

[14] Kim G Kim H Park J and Yu Y 2011 Vehicle tracking based on kalman filter in tunnel *In International Conf. Inform. Security Assurance* pp 250-56

[15] Orderud F 2005 Comparison of kalman filter estimation approaches for state space models with nonlinear measurements *In Proc. Scandinavian Conf. Simulation and Modelling* pp 1-8

[16] Sayankar B B, Rangaree P H and Giripunje S D 2010 Filtering of images by kalman filter using vhdl *In 2010 3rd International Conf. Emerging Trends Engin. Technol.* pp 741-44

[17] Iswanto I A and Li B 2017 Visual object tracking based on mean-shift and particle-Kalman filter

Procedia Comp. Sci. **116** pp 587-95

[18]   Wang L, Li L and Kong D 2013 An improved particle filter tracking algorithm based on motion and appearance features *In 2013 International Conf. Comp. Inform. Sci.* pp 110-13

[19]   Maggio E and Cavallaro A 2005 Hybrid particle filter and mean shift tracker with adaptive transition model *In Proceed. IEEE International Conf. Acoustics, Speech, and Signal Processing* pp ii/221-ii/224