Dolphin Inspired Optimization for Feature Extraction in Augmented Reality Tracking

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***Abstract*—Feature extraction has the prominent role in Augmented Reality (AR) tracking. AR tracking monitor the position and orientation to overlay the 3D model in real-world environment. This approach of AR tracking, encouraged to propose the optimum feature extraction model by embedding the dolphin grouping system. We implemented dolphin grouping algorithm to extract the features effectively without compromising the accuracy. In addition, to prove the stability of the proposed model, we have included the affine transformation images such as rotation, blur image and light variation for the analysis. The Dolphin model obtained the average precision of 0.92 and recall score of 0.84. Whereas, the computation time of dolphin model is identified as 2ms which is faster than the other algorithm. The comparative result analysis reveals that accuracy and the efficiency of the proposed model surpasses the existing descriptors.**

***Keywords*—Feature descriptor; dolphin optimization; feature extraction; augmented reality tracking**

I. Introduction

Feature extraction is the function of Machine Learning (ML) algorithm, which identify the significant features present in the image. Feature descriptor or extractor is the model to extract the features in the form of edge, corner, texture, contour, color and shape of the image. These extracted features have to be robust and efficient in affine transformation of the image and it can be done by adopting the handcrafted and learning based model. Feature extraction is used in many applications: (i) Autonomous vehicle:To recognize the objects and predict the distance of vehicle. (ii) Augmented Reality:Feature extraction applied to superimpose the augmented model in real world. (iii) Manufacturing Industry:To identify the defects and ensure the safety of the products. (iv) Medical applications:Feature extraction aids to identify the early detection and diagnosis of the critical diseases. Therefore, many algorithm have been published for various feature extraction applications in recent years. Speeded Up Robust Features (SURF) [1] deploys box filters for the feature extraction in object recognition and tracking. Scale Invariant Feature Transform (SIFT) [2] is an image matching algorithm, used to extract the features present in multiple scale images, the difference of gaussian is utilized for the feature prediction of multiscale images in SIFT. The Binary Robust Invariant Scalable Keypoints (BRISK) descriptor embedded with Bee colony algorithm, adopts the sampling pattern to extract the robust keypoints present in image matching [3]. Moreover, the Histogram of Oriented Gradients (HOG) [4] aid the histogram technique for the feature extraction of image, which enhances the human detection process. In [5] author proposed learning based feature descriptor model for the anamoly detection. They examined the model with 32 datasets and its result provides the accuracy of the model. However, the model encountered the challenge as computation complexity to process the large size of data with affine transformation. To address the above problem, a Rotation Invariant and Globally Aware Descriptor (RIGA) [6] is proposed. RIGA, extract the feature correspondences of the rotation transformation image. This model enhances the rotation in-variant property of point cloud by deploying the Point-Net architecture which consumes the input from a rotated traditional descriptors. Vision transformer embrace the global awareness geometry in RIGA. Therefore, RIGA performs well in both rotation in-variance and global awareness of the descriptor. Nevertheless, its feature prediction lags in additional transformation properties such as scale, light and occlusion transformation. To deal these challenges, Fencher Multiscale Local Descriptor (FMLD) is proposed. FMLD extract the features from light illumination image. The model uses magnitude and angle fusion for feature prediction. The FMLD performs well in occlusion and light variation. However, this model has the limitation in computation complexity [7]. The computation complexity problem has been addressed in Superpixel-based Brownian Descriptor (SBD). Integration of superpixel with brownian model provides the internal structures of the Hyper Spectral Image. This method extract the efficient spectral spatial features. This hybrid model reduces the computation complexity [8]. The artificial bee colony algorithm is implemented to extract only five features, which achieve 98.8 % of accuracy to detect cyberattacks [9].

Outlier detection using projection pursuit is one of the techniques, which has not been used so far in the feature extraction. However, the authors of [10] have developed four novel feature selection techniques using the concept of outlier detection and projection pursuit by exploiting the bio-inspired algorithms. The method seemed to outperform the stae-of-the art techniques with an improvement rate ranging between 0.76% and 36%.

Hence, the descriptor is processing with more number of images and datasets so it consumes more computation. There is a trade-off between accuracy and computation in feature descriptor. So researchers are working in this challenge to improve the feature extraction model. However, with respect to the application we can modify the trade-off. Since, the feature can be in any form as mentioned earlier in this section, it is important to normalise or optimize the model.

One of the main challenge of feature extraction is to diminish the data complexity. We proposed the new model dolphin optimization to extract the essential feature with effective computation. The main contribution of the paper is:

- The two filters are proposed to calculate the gradient

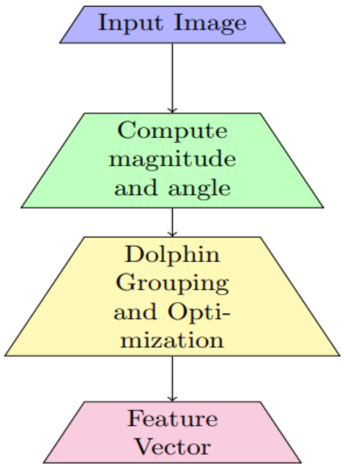


Fig. 1. Dolphin model process flow diagram.

magnitude and orientation of the pixels.

- The spatial location along with magnitude and angle are minimized to measure the similarity in groups.
- In each group feature is formed based on dolphin inspired model.
- The feature is extracted using dolphin optimization.

A. Organization of the Research

The paper is organised as follows in Section II, the related bio inspired optimization models are discussed. In Section III, the dolphin inspired feature extraction methodology is included. Section IV discusses the results and validation of the model followed by a conclusion in Section V.

II. Related Work

This proposed work discuss about the optimization of feature extraction model. Wherefore, here we discuss the recent work related to the subject. In [11] author proposed Principal Component Analysis (PCA) in edge feature extraction for 3D point cloud. This model uses the covariance matrix to predict the features. The PCA is embedded for the optimization of the feature selection. The accuracy of the PCA is compared with traditional method. The PCA model surpasses the traditional model in feature selection. Besides the PCA model a dual correlate, course fine optimization technique is also involved in the feature extraction. This dual correlate model extract the feature in two level such as course and fine level which refines the feature selection process [12]. [13] author designed a locality based approach for the feature selection. It can create the local topology structures to identify the robust features. It identifies the features by matching the similar objects between two images and it removes the mismatch to obtain the robust matching. In addition to that, recently many bio-inspired models are proposed for the feature optimization which we discuss in next section.

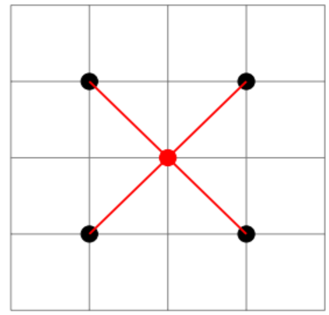


Fig. 2. Filter design to compute gradient in vertical image plane.

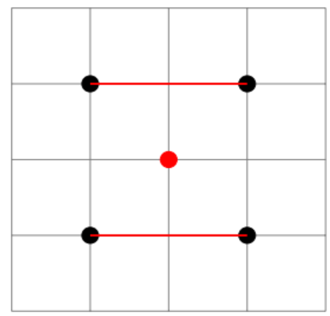


Fig. 3. Filter design to compute gradient in horizontal image plane.

A. Bio-Inspired Optimization in Feature Extraction

Many Bio-inspired optimization model have been implemented to enhance the accuracy of the feature extraction. In this paper [14], author published support vector machine algorithm by incorporating the ant colony optimization which identifies the early stage of cancer detection. The abnormal cells or features are recognized by gray level co-occurrence matrix then ant colony optimization is applied to extract the significant features. In [15] author applied the Binary whale optimization algorithm to enhance the accuracy of the feature selection in molecular descriptor. This molecular descriptor contains all the information about molecule in drug market. So the prediction of prominent features is necessary to avoid the heavy computation of the descriptor. This can be achieved by the innovation of non-linear time varying sigmoid function in whale optimization. Therefore, this whale optimization improves the feature selection in molecular descriptor. Further, to optimize the texture features, the Binary particle swarm optimization technique [16] is implemented to select the desired texture features from an optical character recognition system. This system accepts only the text, so to automate the model we need to suppress the non text from the text, it can be done with the help of swarm optimization model. Similarly, in [17] the author proposed a Crow search algorithm to select the essential feature from face image using the neural network model. The Local ternary pattern with SURF based hybrid descriptor is used to predict the features in the model. Crow optimization act as a prominent role to achieve the extraction of optimized features with the accuracy of 95% for face recognition models.

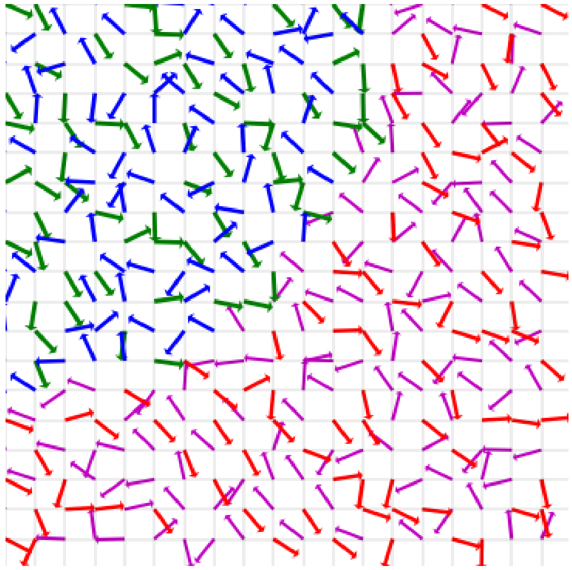


Fig. 4. The lines with different color intensities describe the dolphin grouping - 4 groups - based on spatial distances, angle and magnitude of pixel intensities in image plane.

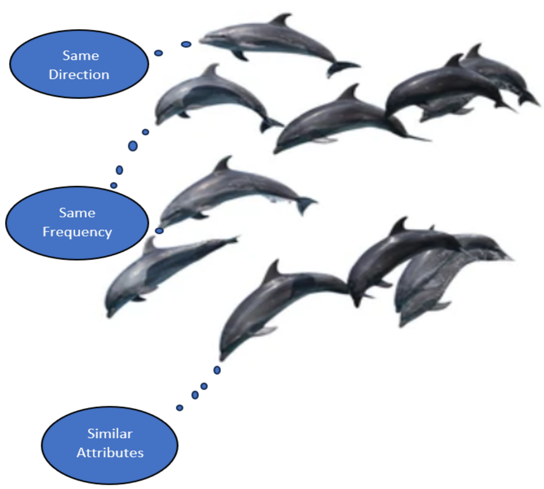


Fig. 5. Dolphin attributes mentioned in image to form a group.

III. Methodology

This section presents the detail of the proposed model. Our methodology consist of three stages: Social secrets of Dolphin, AR tracking and Dolphin dynamic optimization. The secret behaviour of dolphins are discussed in Section III-A for the better understanding of the dolphin optimization. In Section III-B provides the detail of the AR tracking system along with filter design implementation and finally Section III-C describes the dolphin implementation in feature extraction.

A. The Social Secrets of Dolphins: How These Clever Creatures Form the Groups

Dolphin and human have many similar characteristics, which motivated to adopt the dolphin behaviour in feature extraction. Dolphin is a social animal like human so it can communicate, eat and stay together as a group. How it forms the group is really an impressive and unique nature of dolphin. After many studies about the dolphins we come to the conclusion that the dolphin can form a group according to the factors such as species, spatial proximity, behaviour, food habits, age and family association [18]. A single member in a group is the sample to understand the behaviour of the group. Moreover, dolphin can interact with each other through their signature sound [19] and body languages. This way of communication is helpful to share their thoughts between them. The dolphin group size, is different with respect to the food availability region. Usually, each group has the maximum limit of 30 members however, mega-group consist of 1000 members. This mega-group can form instantly where it is attracted by the abundant food. Dolphin studies says, it has preferences to meet the individuals and it can remember and identify them even after long period of separation. The reason of group formation is for their safety and growth.

From the understanding of the dolphin behaviour it narrates few points with respect to the creation of group:

- Dolphin can form a group to protect themselves.
- The signature whistles are used for communication between individuals.
- The whistle sound is composed from the hereditary and each dolphin has its unique vocals with respect to the certain range of frequencies.
- This sound helps to identify their location.
- The similarity in behaviours are attracted to be a member in the groups.

These behaviour of dolphin is implemented in our model to extract the features and the dolphin group is shown in Fig. 5. In the upcoming section, we will discuss the process flow of AR tracking with filter design and the necessity of dolphin dynamic optimization in feature extraction.

B. Augmented Reality Tracking

AR Tracking system immerse the 3D model in physical world. The Tracking process consist of five steps:

1) Pre-processing: Re-size the image to form a uniformity in the analysis.

2) Feature detection: Detector can detect the necessary information as a keypoints from the image.

3) Feature description: The feature vector is manifested by the inclusion of neighbouring pixel surrounded by the keypoint.

4) Feature matching: The feature vector of reference and test image is compared to find the matches in the image.

5) 3D Model: Once the feature is matched in the above stage then in this stage it creates a 3D model.

These above mentioned five stages are the process flow of AR tracking. We focus our work in development of the feature descriptor for AR tracking and the flow diagram of our design is illustrated in Fig. 1. According to the flow diagram, the first stage contains the input image. The image matrix of the input is represented as $I_{M \times N}$. Moreover, we designed two filters to measure the gradient changes in vertical and horizontal plane of the image. The pixel point of interest is considered as $I_{m,n}$. The m is varied from 0 to$M$ similarly, the n changes from 0 to N in image. The vertical and horizontal filters are shown in Fig. 2 and Fig. 3 respectively. From the figure, the pixel point of interest is shown in red color and the four neighbouring pixels are indicated by black for the visualization. The red line reveals the relation between those pixels. The gradient changes of two plane is measured as $\mathbf{P}_\mathrm{x}$ and $\mathbf{P}_\mathrm{y}$ from Eq. (1) and Eq. (2).

$$\begin{aligned}\mathbf{P}_\mathrm{x} &= \mathrm{I(m\text{-}1,n\text{-}1) - I(m\text{-}1,n\text{+}1)}\\ &\quad \mathrm{+I(m\text{+}1,n\text{-}1) - I(m\text{+}1,n\text{+}1)}\end{aligned} \tag{1}$$

$$\begin{aligned}\mathbf{P}_\mathrm{y} &= \mathrm{I(m\text{-}1,n\text{-}1) - I(m\text{+}1,n\text{+}1)}\\ &\quad \mathrm{+I(m\text{-}1,n\text{+}1) - I(m\text{+}1,n\text{-}1)}\end{aligned} \tag{2}$$

The Eq. (1) and Eq. (2) are used to obtain the gradient magnitude and orientation as per the Eq. (3) and Eq. (4).

$$\mathrm{G} = \sqrt{(\mathbf{P_x})^2 + (\mathbf{P_y})^2} \tag{3}$$

$$\Phi = \arctan\left(\frac{\mathbf{P_y}}{\mathbf{P_x}}\right) \tag{4}$$

C. The Proposed Model-Dolphin Dynamic Optimization

The robust feature extraction is the fundamental task of AR Tracking. Hence, the significance of the feature descriptor model is growing, we need to solve the challenge arises to the feature descriptor, that is to identify the stable feature with efficient computation time. In this paper, we provide the design of optimum feature descriptor by incorporating the dolphin optimization model. The main concept of Dolphin Dynamic Optimization is transforming the behaviour of dolphin into image plane for the effective feature extraction using the grouping techniques. The reason for the implementation of dolphin algorithm is how the individuals can combine with its neighbours to form a group is similar to the group of pixels along with its neighbour tends to create a feature. The dolphin key parameters mentioned in the Section III-A is used for the feature prediction. The goal of this study is to group the features precisely. This feature grouping leads to retrieve the shape of the image.

Dolphin model is innovated to predict the shape of the image in a 2-Dimensional space. The dolphin model divide the data points into K groups. The core plan of the model utilize few parameters to form a group such as, image gradient, orientation and spatial location respectively. The image gradient and orientation is obtained from the vertical and horizontal filter mentioned in Fig. 2 and Fig. 3. The gradient and orientation measurements are discussed in Section III-B. Moreover, at this stage the keypoints are ready but its not fit into the shape to retrieve the image. This gap can be fulfilled by the implementation of the dolphin dynamic optimization. The dolphin algorithm works as follows:

- Randomly initialize the dolphin head from the image spatial location.
- The selected head spatial location, gradient and orientation is compared with other data points in the image plane.
- The minimization of the cost function is the criteria to join as a member into the group.
- To fix the head of the dolphin the process is repeats for the R number of iterations until it convergence.
- Then, finally we have the group of features which reflects the shape of the image.

Considering the 8 bit image representation, the gradient magnitude can vary from 0 to 366.6 and the orientation is in the range of 0 to 90°. Assuming that the image dimension is $M \times N$, then the shape normalization is ensured in such a way that M and N correspond to λ_K and δ_K respectively. At the beginning, K spatial locations of the dolphin heads are uniformly spread having the distribution ranging within M and N respectively. Let $\Lambda = \{\lambda_1, \lambda_2, \cdots, \lambda_K\}$ and $\delta = \{\delta_1, \delta_2, \cdots, \delta_K\}$ indicate these initial locations. The cost function accounts the spatial distance, magnitude difference and orientation between dolphin heads and every other pixels as given in Eq. (5).

$$\begin{aligned}\mathrm{J} = \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{k=1}^{K} &\mathbf{r}_k(m,n)\big\{[m-\lambda_k]^2 + [n-\delta_k]^2\\ &+ [G(m,n) - G(\lambda_k,\delta_k)]\\ &+ [\Phi(m,n) - \Phi(\lambda_k,\delta_k)]\big\}\end{aligned} \tag{5}$$

The indicator function $\mathbf{r}_k(m,n) \in \{0,1\}$ is introduced to mention the spatial values m and n at which $\mathbf{J}$ is minimum. As a result, we need to minimize $\mathbf{J}$ by differentiating it with respect to $\mathbf{r}_k(m,n)$ in the first step followed by λ_k and δ_k partially. By doing this way, a group is formed with updated dolphin head position in each iteration. The continuous shift of dolphin head in each iteration leads to identify the head by its optimization function. The update takes place, until a stopping criterion is met. When the group can not identify a new head, it is assumed that stopping criterion is met. According to Eq. (6), $\mathbf{J}$ attains minimum with the indices p and q, so that $\mathbf{r}$(p,q) is 1.

$$\mathbf{r}_k(m,n) = \begin{cases} 1; \quad \text{if} \quad m = \text{argmin}_p; n = \arg\min_q \\ \qquad \Big\{[m-\lambda_p]^2 + [n-\delta_q]^2 \\ \qquad +[G(m,n) - G(\lambda_p,\delta_q)] \\ \qquad +[\Phi(m,n) - \Phi(\lambda_p,\delta_q)]\Big\} \\ 0; \qquad\qquad \text{otherwise} \end{cases} \tag{6}$$

In this way, the dolphin groups are formed to extract the image features. The updation of a new dolphin head positions are given by Eq. (7) and (8).

$$\lambda_k = \frac{\sum_m \sum_n r_{mn} \cdot m}{\sum_m \sum_n r_{mn}} \tag{7}$$

$$\delta_k = \frac{\sum_m \sum_n r_{mn} \cdot n}{\sum_m \sum_n r_{mn}} \tag{8}$$

(a) Graffiti image. (b) House image.

Fig. 6. Input images for test without any transformation.

Algorithm 1: Feature Extraction of Dolphin Algorithm

Input: $\mathbf{I}_{M\times N}$
Output: C
$\mathbf{P_x}$ = I(m-1,n-1)- I(m-1,n+1) +I(m+1,n-1)-I(m+1,n+1)
$\mathbf{P_y}$ = I(m-1,n-1)-I(m+1,n+1) +I(m-1,n+1)-I(m+1,n-1)
Calculate G $= \sqrt{\mathbf{p_x}^2 + \mathbf{p_y}^2}$
Calculate $\Phi = \arctan\left(\frac{\mathbf{p_y}}{\mathbf{p_x}}\right)$
while
  do
  for $m = 1$ to M **do**
    for $n = 1$ to N **do**
      for $k = 1$ to K **do**
        Find **J** using (5)
        Minimize **J** to update $r_k(p, q)$ using (6).
        Update λ_k and δ_k using (7) and (8)
      end for
      $\mathbf{C}(m,n) = \min_{j\in\{1,2,3,\cdots K\}} \mathbf{J}$
    end for
  end for
end while

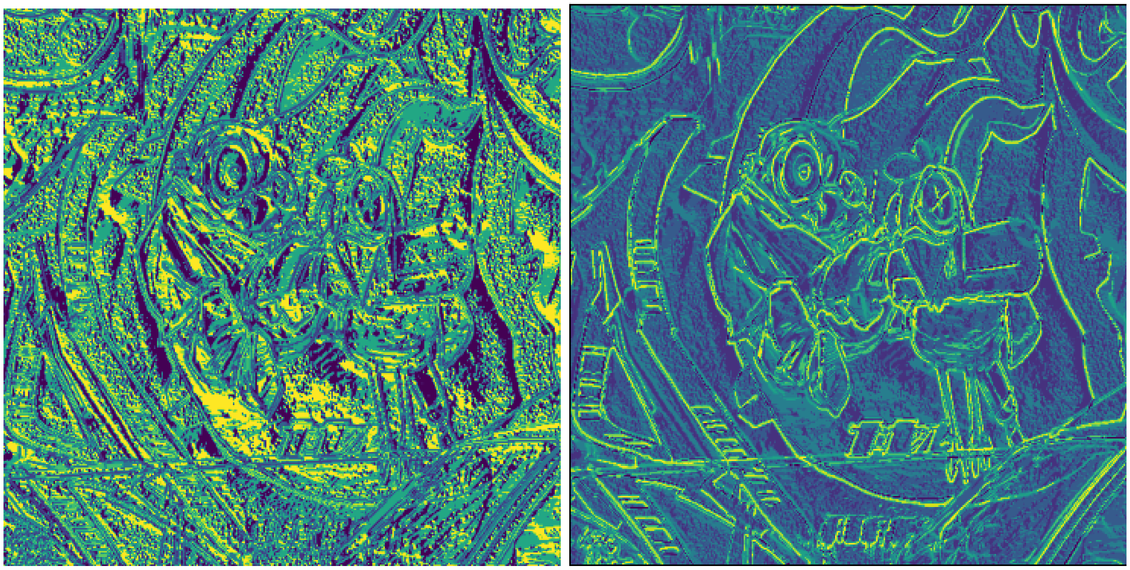
The feature extraction of dolphin model is grouped based on Algorithm 1. The dolphin group formation with respect to the cost function minimization is illustrated in Fig. 4 which shows the line with arrow indicates the output of the cost function which is generated from the minimization of spatial location, gradient and orientation of the pixels. Each color in the plot indicates the different group of the dolphin which is directly proportional to the **J** function. Fig. 4 provides the pictorial representation of the nearest spatial location with similar direction and magnitude belongs to one group. This way we can retrieve the shape of any image from the dolphin optimization model.

IV. Results and Discussion

In this section, we discuss the simulation results of dolphin optimization algorithm with respect to feature extraction. The input images are adopted from two public datasets which is available in the following link [https://www.robots.ox.ac.uk/] and [http://sipi.usc.edu/database/]. We utilized two benchmark to evaluate the dolphin algorithm, namely accuracy and efficiency of the model. The accuracy of the feature prediction is measured using precision and recall score. The efficiency is defined from the processing time of the feature extraction model which is denoted as computation time. At initial stage, graffiti and house image both are tested to measure the accuracy of the features. These images are consist of different structures, hence its feature extraction is evaluated. In addition to that, the affine transformation image also included to validate the robustness of the design. The robustness of the feature extraction with respect to viewpoint variation, blurred image and light variation is measured using graffiti, bike, and car image respectively. Moreover, the transformed image such as graffiti is rotated with particular angle, bike image is tested with the noise, and car image light intensity is reduced for the validation. The experiments are simulated using python 3.10, with NVIDIA, 11th Generation i7processor.

A. Original Image Features

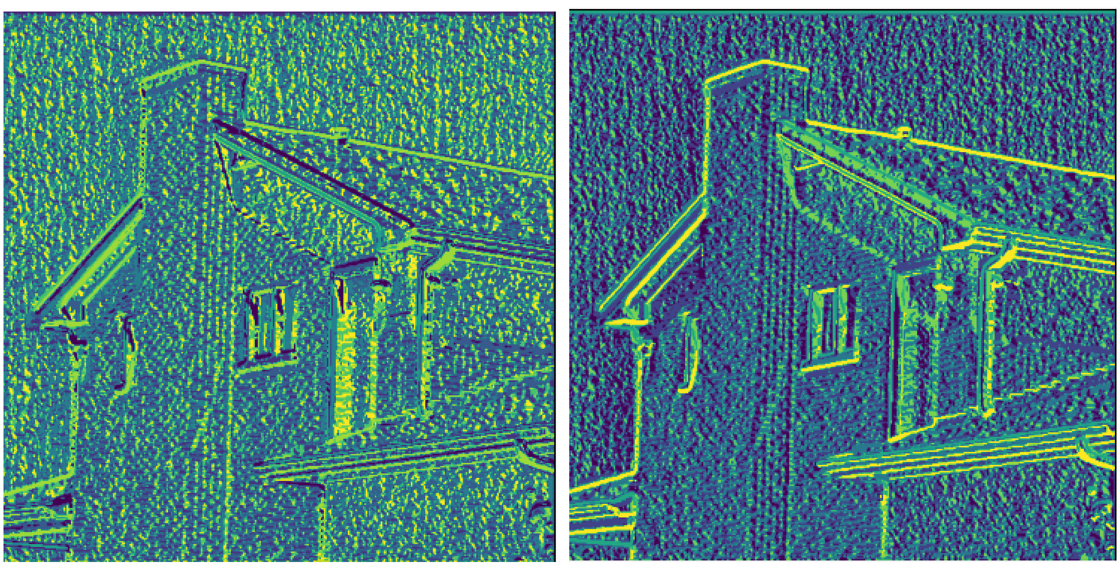
In Fig. 6 shows the original image of graffiti and house image which is considered as the reference because it is not given into any transformation. Graffiti and house image



(a) Feature extraction of dolphin for group size=6.

(b) Feature extraction of dolphin for group size=8.

Fig. 7. Feature extraction of graffiti images.



(a) Dolphin feature extraction of house image for group size=6.

(b) Dolphin feature extraction of house image for group size=8.

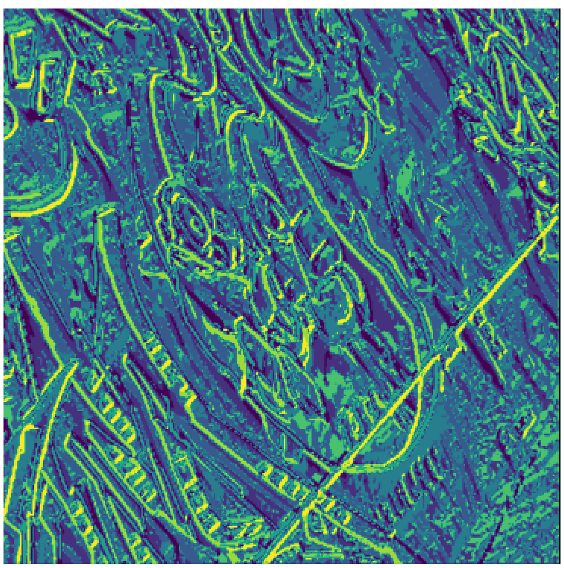
Fig. 8. Feature extraction of house images.

features are compared to provide the robustness of the dolphin model. Although, graffiti has more number of edges than the house image, dolphin model predicts the feature very well for both the images. For the detail analysis of feature extraction the graffiti and house image features are extracted with different group size. Initially, group size is low then we gradually increases the group size to verify the performance of the model. For the visualization of the feature, we have included two group sizes which is shown in Fig. 7a it carries the group size of 6 and Fig. 7b holds the group size of 8. The elbow method is aided to show the optimal group value of dolphin algorithm which is shown in Fig. 13. It indicates the optimum value of the group is 8. Therefore, the optimum number of group size indicates the accurate feature prediction. From the results of Fig. 7b and 8b we can visualize the shape of the image, hence it proves all the edges are completely retrieved from the original image with respect to the cost function of **J** forms a group. Each group in image is illustrated with different color according to the intensity variation. The yellow color has high intensity, then the level of intensity is decreases with the different color representation such as green, blue and purple respectively. Each color has two different groups with the color deviation hence the total group is 8. Thus reflects in an image as an edge color from yellow to purple.

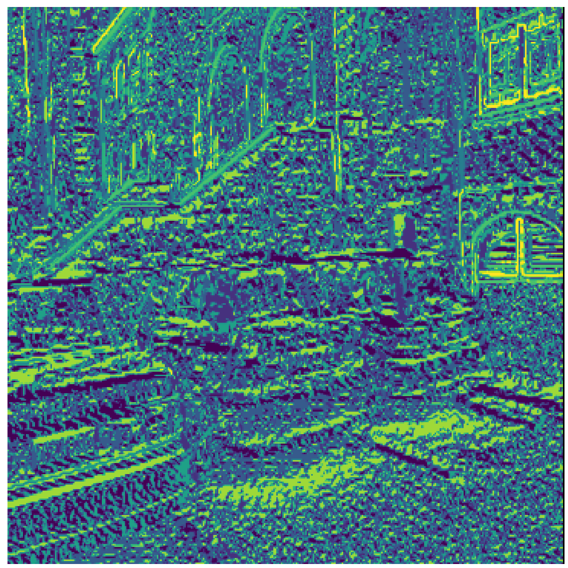
(a) Graffiti image viewpoint varied by 40°.

(b) Car light variation by gamma compression.

Fig. 9. Viewpoint and light variation of original images.



(a) Feature extraction of graffiti in view point variation.



(b) Feature extraction of light variation in car image.

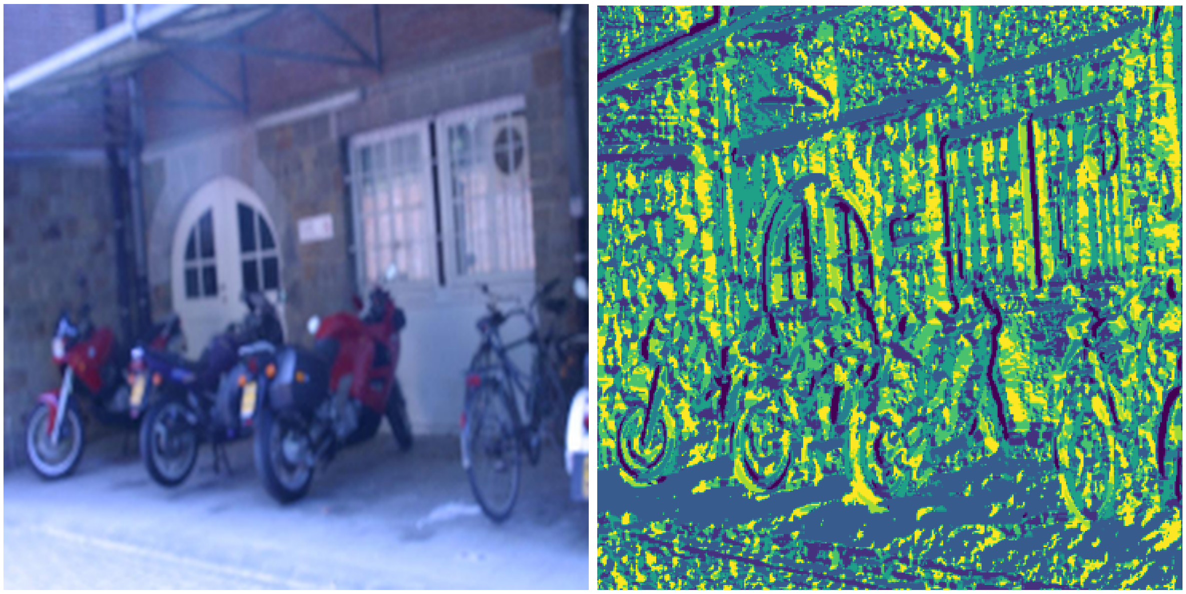
Fig. 10. Viewpoint and light variation of image features.

TABLE I. THE AVERAGE PRECISION AND AVERAGE RECALL: A COMPARISON OF PROPOSED ALGORITHM WITH OTHER ALGORITHMS

Descriptor	Average Precision	Average Recall
Dolphin	**0.92**	**0.84**
HOG	0.82	0.76
BRIEF	0.73	0.65
BRISK	0.63	0.59
SURF	0.57	0.44

TABLE II. COMPARISON ANALYSIS OF COMPUTATION TIME

Feature Descriptor	Computation Time(ms)
Dolphin	**2.0**
HOG	3.8
BRIEF	5.6
BRISK	13.7
SURF	18.6



(a) Blur variation in bike image.

(b) Feature extraction of dolphin in blur variation.

Fig. 11. Blur image and its feature extraction.

B. Transformation Image Features

The image transformation, indicates transformation of image from one form to other. For the analysis, we resized all the transformation test image into the size of 512×512 and the group size is chosen as 8. We used three transformation, namely, rotation, blur variation and light variation. The goal of this testing is to prove the robustness of the dolphin model in feature prediction with affine transformation. Fig. 9a shows the 40°rotated image of graffiti, hence it is created by view-point variation of the camera is given as 40°. In case of car image the light intensity is decreased from the original image to test the illumination in-variance of our proposed model refer Fig. 9b. In addition to that, the bike image which is shown in Fig. 11a is blurred due to the movement arises between scene and camera. The Fig. 10a shows the output of the rotated image which is reflected with the extraction of all the edge features present in image so our model outperforms in rotation in-variance. Moreover, the feature prediction in light intensity variation is very difficult to process whereas, our model reaches the success to regain the car image from light variation and its shown in Fig. 10b. However, the blur variation shown in Fig. 11b is lagging in accuracy of the feature prediction than the other transformation but still it can retrieve the shape of the image. Fig. 12 shows the feature extraction using dolphin method after compressing the original image. The 80% of compression is applied to the original image and then the features are extracted. The result verify that there is no compromise in extracting the features even after compression. Therefore, in accordance with affine transformation our model produces best results for rotation variation than light and blur variation. Even though our model provides with good accuracy of feature extraction, still there is a space for improvement of the model.

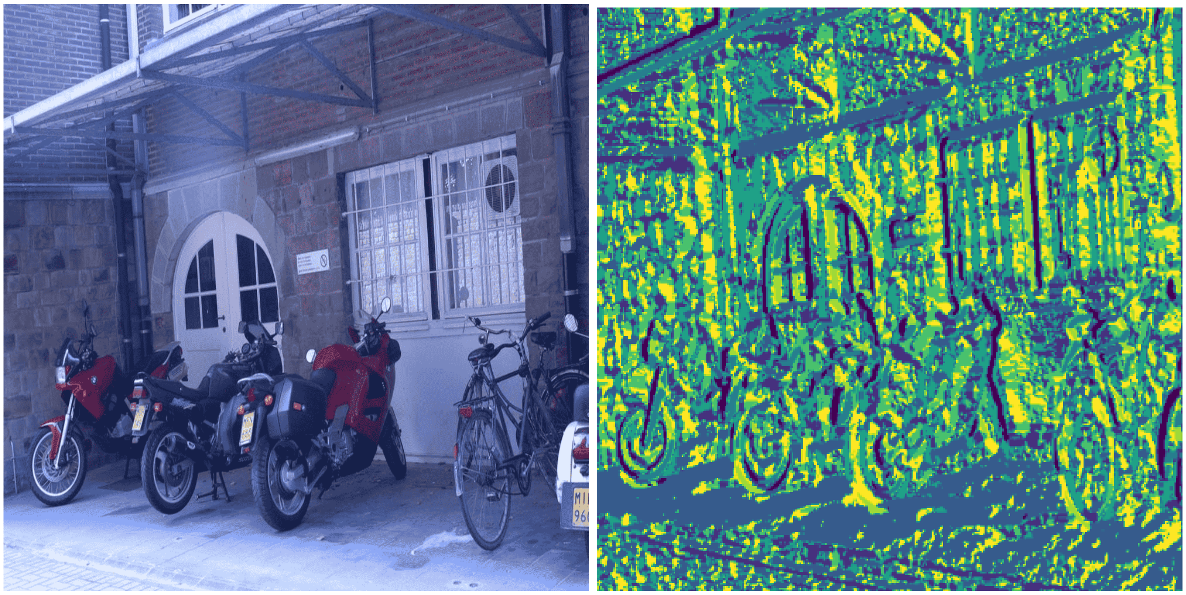
For the quantitative analysis, we have included the precision and recall value of the different descriptors to evaluate the accuracy of the model. The validation image is taken as the graffiti with the size of 512×512. The dolphin model is compared with recently proposed feature descriptors, namely, HOG, BRIEF, BRISK and SURF. The true prediction is measured using the precision and recall provides the correct identification of features in image the evaluation results are given in Table I. From the results dolphin model achieves good results than the existing models. The second largest value scored by BRIEF, its precision and recall value is better than BRISK and SIFT. Therefore, it concludes dolphin extract all the necessary features to retrieve the image.

In addition to that, to prove the efficiency of the model the computation time is measured. The computation time of the dolphin model is measured from $\mathcal{O}(M*N*K*R)$. The M and N are the size of the image and K indicates the group size then R is the iteration of the process. The system we used for the simulation is capable to run 5000 millions FLOPS per second. The model validated the results with the image size, number of groups and iteration value are assigned in such a way that, $M = 512$, $N = 512$, $K = 8$ and $R = 500$ then 1048576000 FLOPS are needed according to our model design. Therefore, from this validation, we can obtain the computation time of dolphin as 2.0ms which is faster than other algorithms as perceived from the Table II.

V. Conclusion

This article, proposed a optimized feature extraction model for AR tracking along with affine transformation such as rotation, blur and illumination variation using dolphin algorithm. Precisely, dolphin optimization contains two stages, namely, gradient computation and dolphin grouping.

We proposed two filters for the gradient measurement of the image pixels. Further, to measure the optimized grouping with respect to dolphin behaviour we tested the



(a) Compression in bike image.

(b) Feature extraction of dolphin in compression artifacts.

Fig. 12. Compressed image and its feature extraction.

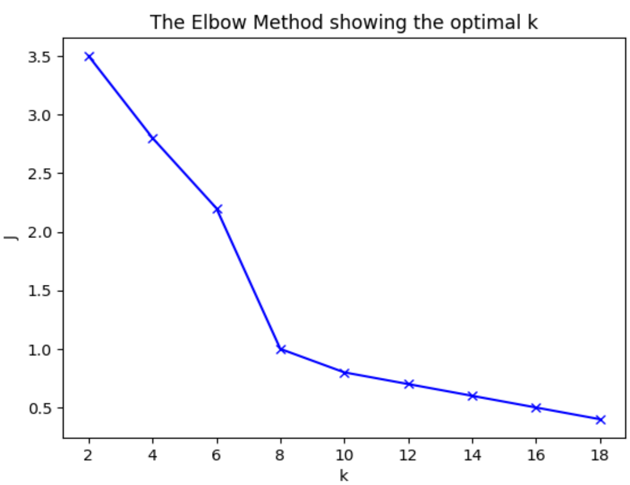


Fig. 13. Filter design to compute gradient in horizontal image plane.

image with several group size for the validation of the feature extraction. From the results we can conclude the optimum group size is identified as 8 for the robust feature prediction. The computation of the model surpasses the existing model is observed from the measurement. The accuracy of the image retrieval is measured in terms of precision and recall. Dolphin model outperforms other existing algorithm in terms of accuracy and efficiency. In future, the scale variation and partial occlusion can be included for the better development of feature extraction model in AR tracking.

Acknowledgment

The authors would like to thank god almighty for the support and thanks to our Vellore Institute for providing the facilities to finish our research.

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