USAGE OF MULTIPLE FEATURES, ENHANCED FEATURE SELECTION ALGORITHM AND ENSEMBLE CLASSIFIER TO IMPROVE THE DETECTION OF MOTORCYCLE RIDERS WITHOUT HELMETS FROM VIDEOS

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ABSTRACT

The increasing mortality rate in motorcycle accidents has forced government to introduce helmets as mandatory safety equipment. In this work, an automatic helmet recognition system is proposed to group motorcyclists as helmet wearers and non-helmet wearers. The proposed system has three main steps, namely, moving object detection, motorcycle detection and non-helmet wearer detection. his work first extracts multiple features from the moving objects. The moving objects are extracted using frame difference method. During motorcycle and helmet identification, multiple features are extracted, from which optimal features are extracted using a method that combines Maximum Relevant Minimum Redundant algorithm with two hybrid methods combining genetic algorithm and ant colony optimization methods. The optimal feature vector is then used to train an ensemble system that uses SVM as base classifier. The performance of the ensemble system is improved through the use of a preprocessing step that used connected component labeling and visual features to first detect candidate motorcycle vehicles. Experimental results proved that the proposed algorithm improve both motorcycle and helmet detection and produced a high accuracy of 99.1% during motorcycle detection and 96.50% during helmet detection.

KEYWORDS : Automatic Helmet Detection, Automatic Motorcycle Identification, Multiple Features, Hybrid Feature Selection,Genetic Algorithm, Ant Colony Optimization, Ensemble Classification.

1. INTRODUCTION

Motorcycles form an integral part of todays' transportation system and the number of person's using motorcycles is increasing day-by-day. The reason behind this increase is due to its affordable price, great fuel economy and ease of handling. According to Konlan*et al.* (2020),around 770 million motorcycles are on the roads worldwide and accidents involving them is more than 3,80,000 deaths worldwide. This makes motorcycle accidents an important area concerning public health and safety. V2V (Vehicle to Vehicle) communication and infotainment systems are recent technological trends used for motorcycle safety. Additionally, government, in an effort to reduce road accidents involving motorcycles, introduced helmets as a mandatory safety equipment. Head injuries are the leading cause for deaths in road accidents and helmets protect rider's head during impact, thus reducing reduced casualties by more than 50% (Berry, 2020). However, unfortunately, not many motorcyclists abide this mandatory helmet rule. Traffic police and law offices continuously monitor traffic to identify persons who do not wear helmets while driving. As manual inspection of traffic is very difficult, modern video surveillance systems are used, which produce hours and hours of video, that are examined by human experts, to apprehend helmet rule violators. As the error rate of this human-assisted scrutiny system is high, automating the task of identifying helmet and non-helmet wearing motorcyclists is much desired.

Automatic Helmet Recognition System (AHRS) from videos aims to identify motorcycles with drivers not wearing helmets. The design of AHRS involves three major stages, namely, background modeling stage, motorcycle detectionstage and helmet detection stage. The result of AHRS can be used by an automatic license plate recognition system, which convertsthe motorcycle license plate number to text. This text is then used to get details regarding the motorcycle ownersso as to take legal actions against them. This paper focuses on stages 2 and 3. The second stage is concerned with motorcycle detection while the third stage is focused on grouping helmet wearers and non-helmet wearers. Both the stages use machine learning classification algorithms and this work proposes methods to improve the classification performance.

One proven method for improving the accuracy of a classifier is to use multiple feature sets in place of single feature vector (Dai *et al.*, 2019). Therefore, this paper uses multiple feature extraction methods during the construction of feature vectors, both during vehicle classification and helmet detection. For this purpose fivetypes of features, namely, Linear Binary Pattern (LBP), Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), Haralick Features (HF)and Circular Hough Transform (CHT), are extracted. One major drawback while using multiple features is the high dimensionality. This issue is solved using feature selection algorithm that is designed as a 2-step method, where the first step uses a filter-based approach (Maximum Relevant Minimum Redundant or MRMR) as preprocessing and helps to remove the redundant features, while the second step uses a hybrid that combines Genetic Algorithm (GA) and Ant Colony Optimization (ACO) to construct the final fused optimal feature vector. The usage of anensemble classification system is proposed for motorcycle and helmet detection. Both motorcycle detection and non-helmet wearers are identified using the same set of features and classifier.

The rest of the paper is organized as follows. Section 2 describes the algorithms proposed for optimal feature vector construction and classification. This section also described the methods used for segmentation and tracking of detected motorcycles. Section 3 evaluates the proposed algorithms and studies its effect on vehicle detection and non-helmet wearer detection. Section 4 concludes the work with future research directions.

2. METHODOLOGY

The AHRS begins by detecting the moving objects in the input traffic video. From the foreground objects, the second step constructs the optimal feature vector. This process consists of subtasks like feature extraction, fusion and selection. Using the salient features from second step, the third step uses an ensemble system to identify motorcycle vehicles and other moving objects. The final step of AHRS considers only the identified motorcycle regions and ignores the rest of the moving objects. The same set of features and feature selection algorithm is applied on the top ¼ region of the detected region, as helmets has to be detected from the head region of the driving person. This feature vector is then used to train the ensemble classifier to separate non-helmet wearers from helmet wearers.The steps involved in AHRS are shown in Figure 1.The moving objects are detected (Stage 1) using the frame difference method.

2.1. Motorcycle Detection

The second stage of the proposed AHRS focuses on the segmentation of motorcycles from the input video. The automatic motorcycle detection is done using three steps, as listed below.

- Preprocessing
- Feature vector generation
- Motorcycle detection

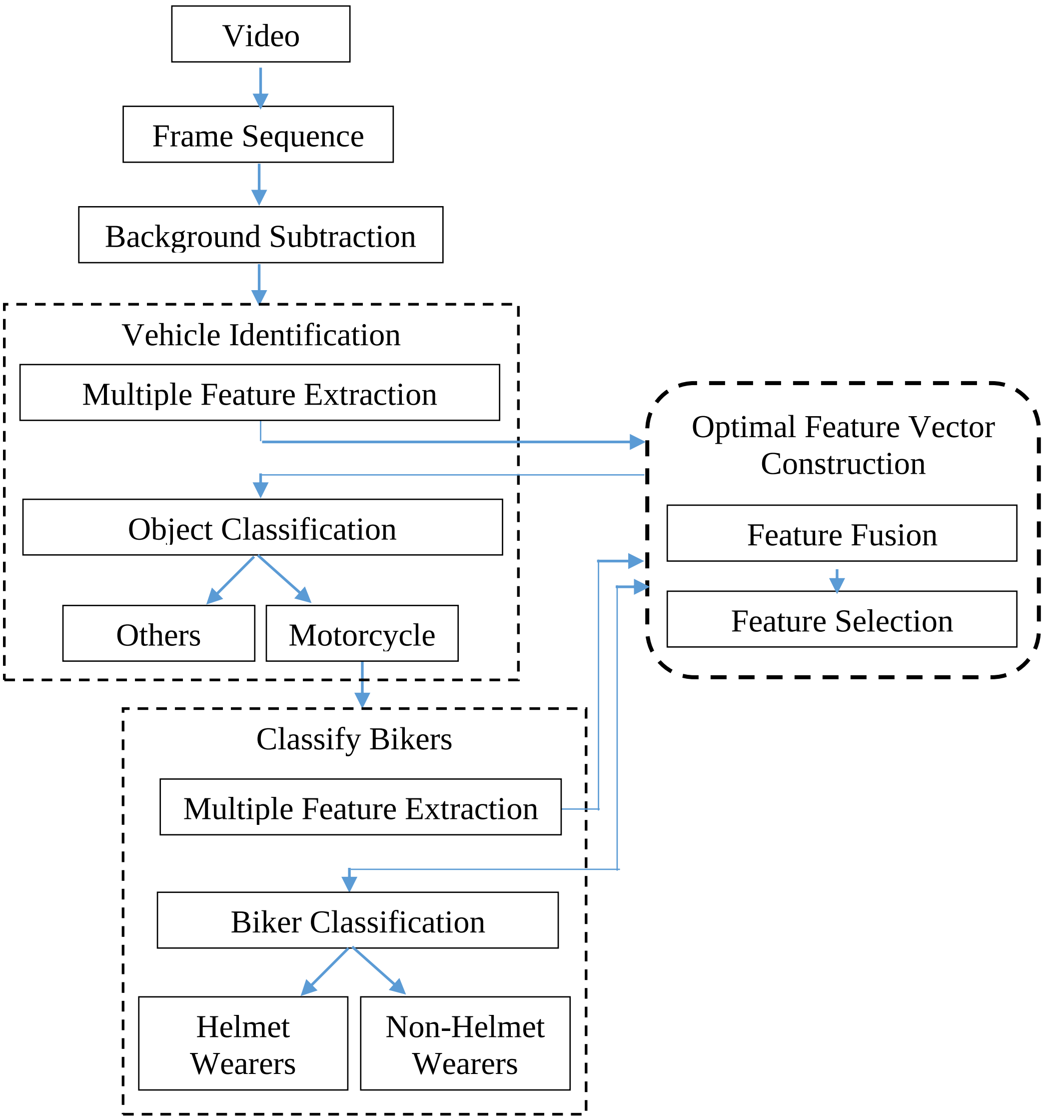


Figure 1 : AHRS Framework

2.1.1. Preprocessing

The preprocessing method proposed is focused on reducing the computational complexity of automatic motorcycle detection. For this purpose, a Connected Component Labelling (CCL) method (Dillencourt*et al.*, 1992) is first used to obtain all the connected regions as bounding box, from the foreground objects detected. Then, for each object detected, three visual features are extracted. They are, length (L), width (W) and pixel ratio (PR). According to Ku et al. (2008), an object can be taken as motorcycle if Equation (1) holds, where m denotes millimeter.

$$2m < L < 4m \text{ and } 1m < w < 2m \text{ and } PR > 0.6 \quad (1)$$

All the objects satisfying the above condition are treated as motorcycles. This step reduces the number of vehicles analyzed, thus successfully reducing the computational complexity of the classifier that detects motorcycle. The method used in Task 1 is referred to as Detection using CCL and Visual Features (D_CCLVF) in this work.

The efficiency of detecting riders not wearing helmet depends heavily on the accurate detection of motorcycle. In order to eliminate the misclassifications from preprocessing, the next step uses a machine learning classifier to group vehicles as motorcycles and other objects. To improve the performance of the machine learning classifier, an optimal feature vector is constructed and used with ensemble classifier.

2.1.2. Feature Vector Generation

The construction of a feature vector that best represent the frames is an important task, whose result has a great influence on the classifier performance. The feature vector constructed should have an unique set of informative or relevant features. In this research work, this desired feature vector is generated in two steps.

a) Step 1 : Feature Extraction
b) Step 2 : Feature Fusion
c) Step 3 : Feature Selection

The algorithms proposed for the above two steps are the same for both desired vehicle (motorcycle) identification and non-helmet wearers identification. As mentioned earlier, this work proposes the use of multiple features along with a hybrid feature selection algorithm for this purpose.

(a) Feature Extraction

As mentioned earlier, five sets of features are extracted from the objects detected during background subtraction. They are, LBP(Ojala*et al.*, 1996), SIFT (Kim and Dahyot, 2008; Bay *et al.*, 2008), HOG(Dalal and Triggs, 2005), HF (Haralic*et al.*, 1973)and (Silva *et al.*, 2013). These features were selected so that the final feature vector can characterize the shape, texture and gradient of the frame and can work independent of scale, rotation and illumination variations thus, provide robustness against varying conditions.

The LBP feature is a texture descriptor. The LBP feature extraction algorithm assigns a label to a pixel by comparing it with its circular neighboring pixels and labels it by assigns a unique number, which is estimated using Equation (2).

$$f = \sum_{p=0}^{P-1} s(gr_p - gr_c), \text{ where } s(gr_p - gr_c) = \begin{cases} 1 & gr_p \geq gr_c \\ 0 & \text{Otherwise} \end{cases} \quad (2)$$

In the above equation gr_c and gr_p are the gray scale values of the central pixels and its neighbouring pixels respectively, s is the thresholding function that assigns a binary value to each pixel and p is the number of neighbours.

SIFT features are used to capture the keypoints of the frame. From each key point, a bag of words technique is used to create a vocabulary. Mapping SIFT descriptors to this vocabulary results with a feature vector that can determine the similarity between frames.

HOG descriptors, the third extracted feature, is used to extract information regarding the local shapes through histogram of oriented gradients. The final HOG descriptor is a one dimensional array of histograms, extracted from the frame that is represented by intensity gradients. This method has the advantage of able to work without aprior edge position knowledge

The HF are also used as texture descriptors and the most widely used statistical method used to analyze texture and the group of methods proposed were termed as Gray Level Co-occurrence Matrix (GLCM). The GLCM uses co-occurrence matrix to extract texture features using statistical equations. A discrete wavelet transformation based texture features were considered in this work. Usage of DWT can increase the quality of the features extracted and can also reduce the time complexity involved with the conventional GLCM-based texture feature extraction. The features extracted are entropy, energy, contrast, homogeneity, coarseness, contrast and degree of directionality. A set of seven descriptors were estimated from each co-occurrence matrix evaluated at $\theta = \{0° ,45° , 90° , 135°\}$ with unit distance (i.e, $d = 1$). The final descriptor is formed by concatenating the features extracted.

The final set of features are extracted using CHT. This is used to find geometric shapes, like circles, lines, ellipses, from the frames. As helmet shape more like circles, they are focused in this work. The CHT uses a voting method to detect circles in the frames. The resultant votes are attributed to points that may be possible circles in the frames. The votes are accumulated in a vote accumulator vector. When a maximum value is obtained, a possible circle is detected. The CHT method requires the minimum radius and maximum radius and the number of circles as parameters. The circles with high votes in the accumulator are returned as output features.

(b) Feature Fusion

All the above five set of features are combined together using a hybrid algorithm. The first step of this hybrid algorithm is to compute the gray scale version the detected objects by using the distance between the R and G components of the RGB color space. The distance metric used in the Euclidean distance metric. A median filter, with 5 x 5 neighbourhoodpixels, is then used to denoise the obtained gray objects in a frame. A threshold, estimated using Otsu (Otsu, 1979) method, is then used to construct the binary version of the gray foreground image. The Sobel edge detection algorithm (Sobel, 1970) is then used to obtain the edges. At this junction, small regions and other noises are removed using morphological operators. All the above steps are treated as preprocessing step.

After preprocessing, the CHT is first used to extract the 9 best frame circles. Best frame circles are circles which have the best or maximum votes. In the next step, the rest of the four features, namely, LBP, HOG, SIFT and HF are computed by the square circumscribed in each of the selected circles. During extraction, LBP was used on a window of size 3 x 3, thus corresponding to 9 histograms. The 3 x 3 neighbourhood was also used to compute the lablel, which were 0 to 255, as the grayscale frame was used for processing. The HOG feature was extracted using the nine histograms by 9 partitioning windows. A 2-level D4 DWT decomposition was performed firstduring the extraction of haralick features, which results with four subbands, namely, HH, HL,LH and LL. As HH subband contain details mostly regarding noise, this band was ignored during extraction. The seven GLCM features were extracted from the rest of the three subbands. Finally, the SIFT features were extracted. The LBO combined with HOG features from CHT along with DWT-based HF and SIFT features are concatenated to form the final feature vector. The final feature vector obtained is referred to as Fused Feature Vector or FFV in this work.

(c) Feature Selection

Feature engineering is the process that carefully manipulates and selects features with the aim of feeding the classifier with only the most optimal form of input. If the classifier is supplied only with the subset of features that makes accurate classification, then the classifier's burden of dealing with noisy features (redundant and irrelevant) is reduced. The feature selection algorithm aims to find a small feature subset whose size less than the original, while not compromising the classification accuracy. However, in real world scenario, the features extracted may have noisy data, misleading or irrelevant data and redundant data. An optimal feature set is considered as a subset which has no noise, contains only relevant and non-redundant features.

In an optimal scenario, this optimal subset can be found by generating all possible subsets and evaluating each one separately to find the best among them. However, this solution is impractical as the number of computations are very high. For example, the number of combinations to be evaluated will be n!/(m!(n-m)!) and the total number of these combinations is (2^n-2), while extracting m number of features from n frames ($m < n$ and $m \neq 0$). Due to this, a solution that finds the optimal feature set, must be computationally feasible and should offer an trade-off solution between high accuracy and low classification time. This trade-off can be achieved through the use of heuristic or random-search strategies (Singh *et al.*, 2016), but these techniques often reduce the degree of optimally of the final optimal feature set.

As a solution, several population-based optimization algorithms have been proposed. Among them Genetic Algorithm (GA) and Ant Colony Optimization (ACO) have gained wide acceptance (Reddu and Kumar, 2020), as both can produce optimal solution using the knowledge gained from previous iterations. This paper to further improve the process of GA and ACO, proposes a 2-step feature selection algorithm that combines filter-based algorithm with hybrid GA and ACO based feature selection algorithm. The working of the proposed 2-step algorithm Combining MRMR, GA+ACO and ACO+GA (2-MFHF) is shown in Figure 2.

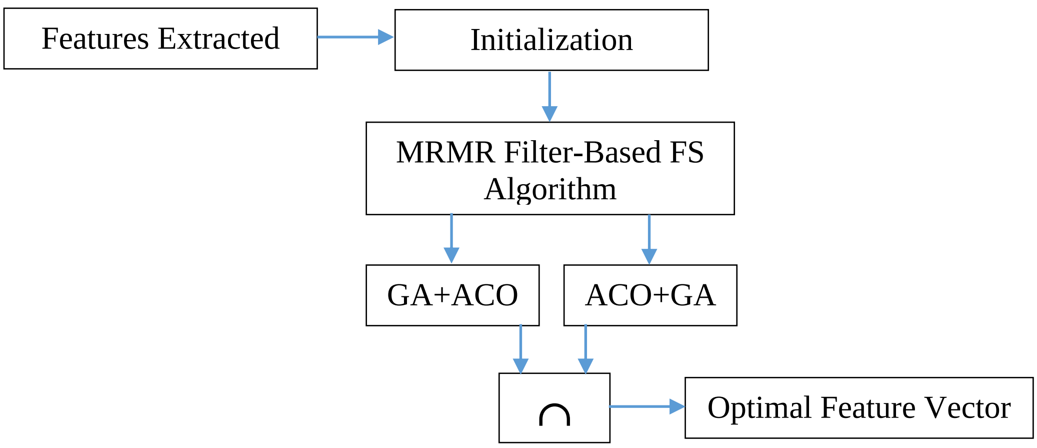


Figure 2 : Proposed 2-MFHF Algorithm

The filter-based algorithm is designed as aprepreocessing step to select only relevant and non-redundant features using MRMR feature selection algorithm. The MRMR algorithm (Ding and Peng, 2003) is a filter-based algorithm that selects features that are most relevant, while simultaneously also ensures minimum redundancy. For this purpose, this algorithm utilizes a correlation based measure called Information Gain (IG). The output of the MRMR algorithm is considered as the set of candidate optimal feature set.

In the second step, this candidate set is used as input to hybrid GA+ACO and ACO+GA algorithms to construct the final optimal feature vector.The two algorithms, GA+ACO and ACO+GA, were designed using the methodology proposed by Benhala and Ahaitouf (2014) (Figure 3).The pseudocode of GA+ACO and ACO+GA are given respectively in Figures 4 and 5.

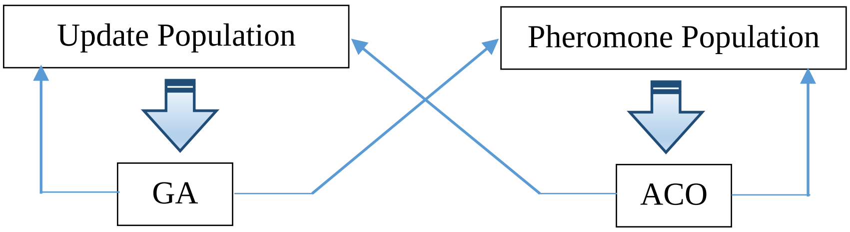


Figure 3 : Methodology Behind Hybridization of GA and ACO

```
Parameter Initialization
Do
    For each iteration
        Perform ACO
        BS = Best Solutions from ACO
    End
    Initialize population using BS
    For each iteration
        Perform GA
    End
OFS1 = Best Solution
END
```

Figure 4 : ACO + GA

```
Parameter Initialization
Do
    For each iteration
        Perform GA
        BS = Best Solutions from GA
    End
    Initialize population using BS
    For each iteration
        Perform ACO
    End
OFS2 = Best Solution
END
```

Figure 5 : GA + ACO

The existing GA+ACO and ACO+GA hybrid schemes are modified to work on the reduced subset produced by the filter-based algorithm. This makes sure that both the algorithm generate a subset that contains optimal features of reduced size. The parameters used to initialize GA and ACO are given in Table 1.

TABLE 1 : PARAMETER SETTINGS FOR GA AND ACO

GA			ACO		
Population Size	:	50	No. of Ants	:	50
Crossover Probability	:	0.9	Evaporation Rate	:	0.1
Mutation Probability	:	1e-4	Quantity of deposit pheromone	:	0.2
			Pheromone Factor	:	1
			Heuristics Factor	:	1

2.1.3. Motorcycle Detection

It has been proved that the use of Ensemble Classification (EC) systems instead of a single classification system is more beneficial (Vijaya*et al.*, 2011; Shvai*et al.*, 2018). In accordance to this, this work also proposes the use of ensemble classification system for identifying motorcycles among the various detected moving objects.The feature vector constructed using the above method is then used to construct an ensemble classification system. An ensemble classification system is a set of base classifiers whose individual results are combined or aggregated for identifying the class to which the test image belongs to. In this work, the ensemble classifier was build using 25 different versions of feature vector created using Adaboost (Chokka and Rani, 2019) subspace sampling method. These vectors are used to construct 25 SVM base classifiers, which were trained to detect motorcycles. The ensemble system uses features extracted from motorcycle objects detected by MD_CCLVF method. The results from the base classifiers is combined using the majority voting aggregation method.

2.2. Helmet Detection

The final stage focuses on identifying motorcycle riders with and without helmets. For this purpose, first the Region of Interest (ROI) has to be identified. In this work, the ROI is the head region of the motorcycle riders. The ROI is defined as the upper portion of the motorcycle region, that is, the top 1/5 of the motorcycle (Shine and Jiji, 2019). This measure was decided after several empirical experiments, which revealed that head region is typically located at the upper 1/5 part of the detected motorcycle region. The first step subtracts this head region from the foreground of the same region to segment the head region. This segmented region is then converted to gray scale and resized to a fixed size of 64 x 64 pixels. The resizing is performed to reduce the time complexity and to improve accuracy. The feature vector construction algorithm described in Section 2.1.1 is used to obtain optimal features from the ROI region. This feature vector is then used to construct the ensemble system (Section 2.1.2), which is used to detect riders who travel with or without helmets.

3. EXPERIMENTAL RESULTS

The proposed non-helmet motorcycles algorithm was evaluated using videos obtained from World Wide Web and two helmet videos (IITH Helmet 1 and IITH Helmet 2)downloaded from https://www.iith.ac.in/vigil/resources.html. Experiments were designed to evaluate both the effect of feature selection and ensemble systems on motorcycle detection and helmet detection. Sample frames from the collected videos are shown in Figure 6.

Figure 6 : Sample Frames

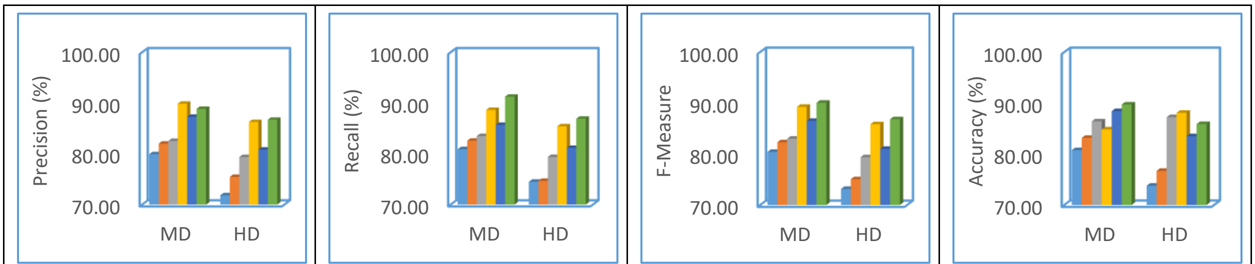
Four performance metrics, namely, precision, recall, f-measure and accuracy, are used to evaluate the algorithms. The experiments were designed to study the effect of the feature extraction algorithm, feature fusion algorithm, feature selection and classifiers used, on its ability to detect motorcycles and non-helmet wearers. The coding scheme during discussion is presented in Table 2.

Table 2 : Coding Scheme Used

Code	Description
Features Extracted	
LBP	Linear Binary Pattern
HOG	Histogram of Oriented Gradients
SIFT	Scale-Invariant Feature Transform
HF	Haralick Features
CHT	Circular Hough Transform
FFV	Fused Feature Vector
Feature Selection	
MRMR	Maximum Relevant Minimum Redundant
GA	Genetic Algorithm
ACO	Ant Colony Optimization
GA + ACO	Hybrid GA + ACO
ACO + GA	Hybrid ACO + GA
2-MFHF	2-step algorithm Combining MRMR, GA+ACO and ACO+GA
Classification	
SVM	Support Vector Machine
EC_SVM	Ensemble Classification System using SVM as Base Classifier
MD_CCLVF + EC_SVM	Detection using CCL and Visual Features + EC_SVM

3.1. Analysis of Feature Extraction and Feature Fusion Algorithms

Figure 7 shows the effect of various feature extraction algorithms on Motorcycle Detection (MD) and Helmet Detection (HD) while using precision, recall, f measure and accuracy as performance measure respectively. The classification algorithm used is the SVM classifier.



(a) Precision (%)	(b) Recall (%)	(c) F Measure	(d) Accuracy (%)

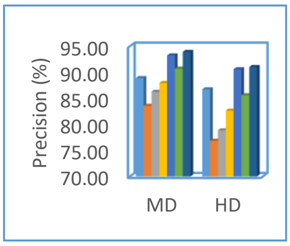
■ LBP ■ HOG ■ SIFT ■ HF ■ CHT ■ FFV

Figure 7 : Analysis of Features and Feature Fusion Algorithm

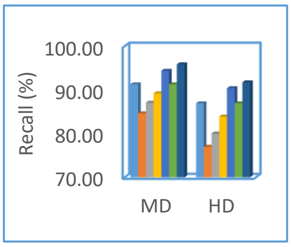
From the above results it is clear that the usage of fused multiple features improve the classification performance with both motorcycle and helmet detection with respect to all selected performance measures. The proposed FFV was able to achieve a maximum accuracy of 89.69% (MD) and 85.88% (HD).

3.2. Analysis of Feature Selection Algorithms

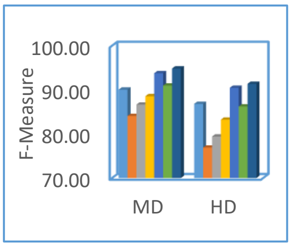
The performance analysis of the feature selection algorithms are shown in Figures 8a to 8d while using precision, recall, f measure and accuracy for evaluation respectively. Again the classifier used was SVM.



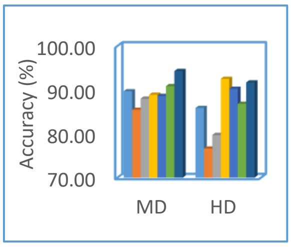
(a) Precision (%)



(b) Recall (%)



© F Measure



(d) Accuracy (%)

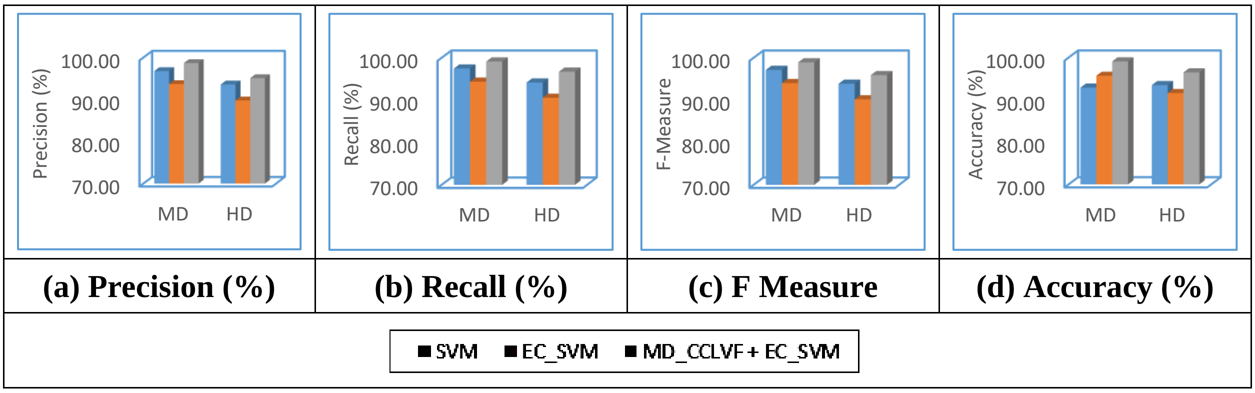
■ FFV ■ MRMR ■ GA ■ ACO ■ GA + ACO ■ ACO + GA ■ 2-MFHF

Figure 8 : Analysis of Feature Selection Algorithms

From the results, it is clear that the performance of both motorcycle and helmet detection has improved while using feature selection algorithms. This is evident by the increased values obtained by the performance metrics when compared to using FFV. Among the existing algorithms, the hybrid algorithms combining GA and ACO show maximized classification performance. However, the algorithm combining the MRMR filter algorithm with multiple hybrid algorithm produced maximum efficiency with respect to all parameters. This algorithm (2-MFHF) produced a high accuracy of 94.30% during motorcycle detection and 91.71% during helmet detection. This improved the performance of SVM classifier by 4.9% and 6.4% when compared with the SVM classifier trained and tested with FFV. The results thus prove that the 2-MFHF algorithm has a remarkable ability to construct reduced feature vector have optimal features, which helps significantly to improve the performance of the classifier.

3.2. Analysis of Classification Algorithms

The performance of the single classifier, ensemble classifier and proposed ensemble classifier on motorcycle and helmet detection is presented in Figure 9, while using precision, recall, f-measure and accuracy metrics respectively.



(a) Precision (%) **(b) Recall (%)** **(c) F Measure** **(d) Accuracy (%)**

Figure 9 : Analysis of Classification Algorithms

Comparison of single and ensemble classifier proves that the ensembling can improve classification performance. However, the above results show that the inclusion of MD_CCLVF further strengthen the fact that the proposed method is more efficient when compared to single and conventional ensemble classification system. The MD_CCLVF combined with EC_SVM produced a high accuracy of 99.10% accuracy with motorcycle detection and 96.50% with helmet detection. Thus, from the results it can be concluded that the classifier MD_CCLVF and EC_SVM trained using the optimal feature subset produced by applying 2-MFHF on VVF provides maximum accuracy during both vehicle detection and non-helmet wearer detection from videos.

4. CONCLUSION

Video analysis for detecting motorcyclists who do not wear helmet is a much desired system, as it could be used to persuade them to practice safe travelling practices. This work focus on detecting non-helmet motorcyclists from video. The proposed system performs detection in three steps, namely, background subtraction, vehicle or motorcycle detection and helmet detection. The frame difference method was used for background subtraction. The proposed automatic helmet recognition system begins with extracting multiple features, namely, LBP, SIFT, HOG, HFand CHT, from the detected moving objects, which are fused to a single vector. A feature selection algorithm combining MRMR algorithm with multiple hybrid GA and ACO algorithm is proposed to select optimal features from the fused vector. This optimal set is then used to construct an ensemble system that used SVM as base classifier. Experimental results showed that the proposed framework is efficient in both motorcycle detection and helmet/non-helmet motorcyclists. Future work is planned to include occluded motorcycle detection and combining the output of the proposed AHRS with automatic license plate recognition system.

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