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# PEDESTRIAN DETECTION USING ARTIFICIAL BEE COLONY OPTIMISED SUPPORT VECTOR MACHINES

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## ABSTRACT

*Wide range of applications and numerous other complexities involved in pedestrian detection makes it a continuous and open area of research. Recently pedestrian detection is getting much more interest and researchers are contributing a lot in this field. Selection of a feature extraction method is very important factor for high recognition performance in human detection systems. In this paper, we propose an efficient self-similarity based human identification using Artificial Bee Colony (ABC) optimized Support Vector Machine (SVM). Initially the background modeling is done from a video sequence. Subsequently, the moving foreground objects in the individual image frames are segmented using the background subtraction algorithm. Then, the morphological skeleton operator is used to track the silhouettes. The MICA based on eigen space transformation is then trained using the sequence of silhouette images. Finally, the proposed system recognizes the human features based on ABC optimised SVM classification. The proposed system is evaluated using gait databases and the experimentation on outdoor video sequences demonstrates that the proposed algorithm achieves a pleasing recognition performance.*

***Keywords*: Pedestrian detection, SVM, MICA, Fast ICA, ABC.**

## I. INTRODUCTION

Pedestrian detection is a canonical instance of object detection. It has various applications such as car safety, surveillance, robotics etc. which enabled it to acquire some much needed attention in the previous years. On the contrary pedestrian detection remains to be a challenging task in the field of object detection. The detection of pedestrian is becoming more significant as the number of pedestrians fatalities are increasing day after day (more than 30999 pedestrians are killed and 430000 injured in traffic around world every year). One of the main concerns of car manufacturers is to have an automated system that is able to detect pedestrians in the surroundings of a vehicle.

To be able to effectively detect pedestrians based on vision is challenging for number of reasons. Few such challenges are pedestrians appear in different backgrounds with a wide variety of appearances and also different body sizes, poses, clothing and outdoor lighting conditions.

Distance of the pedestrian from the camera also plays a vital role as standing relatively far away from the camera may make them appear small in the image. Most pedestrian detectors can achieve satisfactory performance on high resolution datasets; however they encounter difficulties in low resolution images.

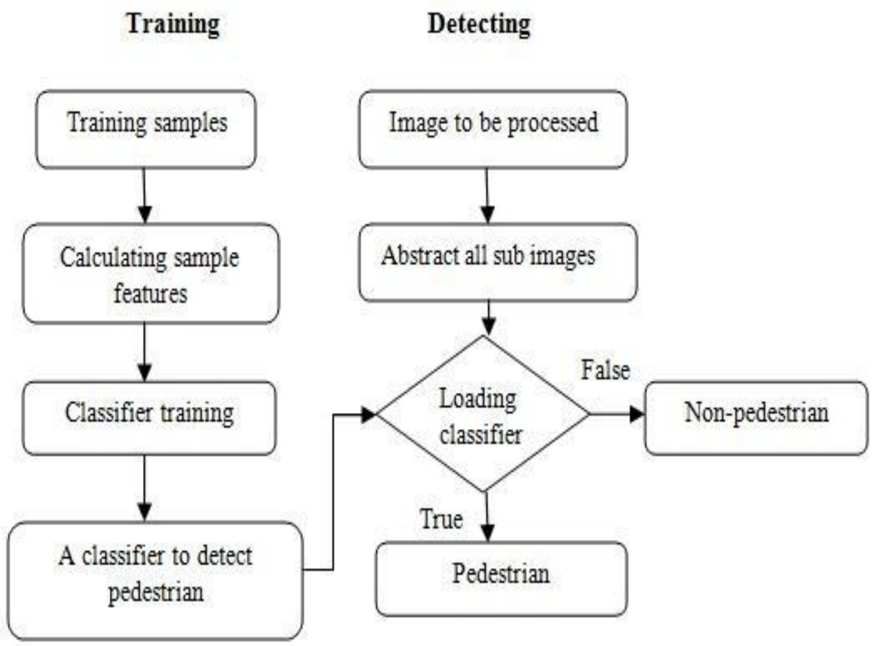


**Fig.1.1 Block Diagram**

Training: In machine learning one of the most important mechanisms is to train this algorithm on this training set. The training set must be different and distinct from the test set. If I use the same data set for both training and testing, the resulting model may not be able to detect unseen data. Hence it is important to separate data into training and test set. Once a model has been created using the training set, I can test the model with the help of the test set.

In the training part the main motive is to extract features of the object so that I can feed the extracted features to the classifier. After normalization the data in the training set I can extract features like Haar-like features or Histogram of oriented Gradient (HOG) features. Certain algorithms like AdaBoost uses a number of training samples to help select appropriate features from the dataset. AdaBoost is able to combine classifiers with poor performance into a bigger classifier with much higher performance.

Once training the system is done and I have a classifier, I can feed the test set to the classifier to check the efficiency of our algorithm. Once the image to be processed is loaded the system can abstract the subimages or the Region of Interest (ROI) from the image and load it onto the classifier. Based on the features extracted in the training phase the classifier will be able to classify whether in a particular image a pedestrian is present or not.

## II. ARTIFICIAL BEE COLONY (ABC)

Artificial Bee Colony (ABC) algorithm was proposed by Karaboga in 2005 for real parameter optimization [1]. It is inspired by the intelligent behaviour of honey bees. The colony of artificial bees consists of three groups of bees: employed, onlooker and scout bees. Half of the colony composed of employed bees and the rest consist of

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the onlooker bees. The number of food sources/nectar sources is equal with the employed bees, which means one nectar source is responsible for one employed bee. The aim of the whole colony is to maximize the nectar amount. The duty of employed bees is to search for food sources (solutions). Later, the nectars‟ amount (solutions‟ qualities/fitness value) is calculated. Then, the information obtained is shared with the onlooker bees which are waiting in the hive. The onlooker bees decide to exploit a nectar source depending on the information shared by the employed bees. The onlooker bees also determine the source to be abandoned and allocate its employed bee as scout bees. For the scout bees, their task is to find the new valuable food sources. They search the space near the hive randomly [2]. In ABC algorithm, suppose the solution space of the problem is D-dimensional, where D is the number of parameters to be optimized.

The fitness value of the randomly chosen site is formulated as follows:

$$fit_i = \frac{1}{1+obj.fun_i}$$

(2.1)

The size of employed bees and onlooker bees are both SN, which is equal to the number of food sources. There is only one employed bee for each food source whose first position is randomly generated. In each iteration of ABC algorithm, each employed bee determines a new neighbouring food source of its currently associated food source and computes the nectar amount of this new food source by

$$V_{i,j} = X_{i,j} + \emptyset_{i,j}\left(X_{i,j} - X_{k,j}\right)$$

(2.2)

Where

i=1,2,…,SN

j=1,2,…,D

k is a solution in the neighborhood of i, Φ is a random number in the range [-1, 1].

If the new food source is better than that of previous one, then this employed bee moves to new food source, otherwise it continues with the old one.

After all employed bees complete the search process; they share the information about their food sources with onlooker bees. An onlooker bee evaluates the nectar information taken from all employed bees and chooses a food source with a probability related to its nectar amount by Equation:

$$p_i = \frac{f_i t_i}{\sum_{k=1}^{SN} f_i\, t_n}$$

(2.3)

The calculation of fitness values of solutions is defined as

$$f_i t_i = \frac{1}{1+f_i} \qquad f_i \geq 0$$

$$= 1 + abs(f_i) \qquad f_i < 0$$

(2.4)

Normalise pi values into [0, 1]

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Later, the onlooker bee searches a new solution in the selected food source site, the same way as exploited by employed bees. After all the employed bees exploit a new solution and the onlooker bees are allocated a food source, if a source is found that the fitness hasn‟ t been improved for a predetermined number of cycles (limit parameter), it is abandoned, and the employed bee associated with that source becomes a scout bee. In that position, scout generates randomly a new solution by:

$$X_j^i = X_{min}^j + rand(0,1)(X_{max}^j - X_{min}^j)$$

(2.5)

$X_{min}^j$, $X_{max}^j$ are the lower and upper borders in the jth dimension of the problem space.

## III. SEGMENTATION

Background subtraction has been extensively used in foreground detection, where a fixed camera is usually used to capture dynamic scenes. In the proposed system a simple motion detection method based on median value is adopted to model the background from the video sequence. Let P represent a video sequence having N image frames. The background P(x, y) can be constructed using the formula:

$$\mathrm{P(x,y)} = \mathrm{median}[\mathrm{P_1(x,y), P_2(x,y), \ldots P_N(x,y)}]$$

(3.1)

The value of P(x, y) is the background brightness to be calculated in the pixel location (x, y) and median symbolizes its median value. In the proposed gait recognition system, we have computed the median value rather than mean value of pixel intensities over N frames, since,

1) Distortion of the mean value for a large change in pixel intensities while the person moves. The median is impervious to spurious values and

2) Median value Computation is comparatively faster than the least mean square value.

Both these statements hold with the assumption that a person continuously moves around over the frames. Subsequently, the extracted background and the original image frames are provided for the foreground modeling. The background subtraction algorithm subtracts the background from the original image frames to obtain the moving foreground objects i.e. human subject in binary.

## 4. MICA

We implement the modified Independent Component Analysis (MICA) to extract and train the features. The purpose of training the silhouettes with the modified ICA is to attain a number of independent components to represent the original human features from a high dimensional measurement space to a low-dimensional Eigen space. ICA aims to identify the vectors that describe data to its best in terms of reproducibility; nevertheless these vectors may not comprise of any effective information for classification, and may eliminate discriminative information.

**Algorithm of Modified Independent component analysis:**

**Step 1**: Data centering. The mean of the observed mixed signal data **X** is computed and the mean is subtracted from the observed data set to make it zero mean.

$$Xc \leftarrow X - E\{X\}$$

(4.1)

**Step 2**: Whitening. The covariance matrix **cov X** of the centered data Xc is computed. The eigenvalue decomposition of **cov X** is performed.

**Step 3**: Fixed-point iteration for one unit. The fast ICA algorithm for one unit estimates one row of the demixing matrix **w** as a vector $W^t$ that is an extremum of contrast functions. Estimation of **w** proceeds iteratively with following steps until a convergence as stated below is achieved.

**Step 4:** Evaluation of second independent component. To estimate the other ICs, Step 3 of the algorithm is repeated for getting weight vectors $W_i$, i = 2,3, … , n.

## V. ARTIFICIAL BEE COLONY OPTIMIZED SUPPORT VECTOR MACHINE

The parameters of the SVM greatly influence the classification results. Inappropriate parameters lead to over fitting or under fitting. Therefore, selecting the optimal hyper parameters is an important step in SVM classification. Parameters include the regularization parameter C, the parameter γ, which controls the bandwidth of the kernel function, and the tube size ε of the ε-insensitive loss function. However, there are no general guidelines for selecting these parameters.

Artificial Bee Colony (ABC) algorithm is a recently introduced swarm-based algorithm in which the position of food source represents a possible solution to an optimization issue and a food source's nectar amount corresponds to the associated solution's quality (fitness) [3]. The number of employed bees or onlooker bees equals number of solutions in a population.

To begin with, ABC generates randomly distributed initial population P (C = 0) of SN solutions (food source positions), with SN denoting employed or onlooker bees size. Each solution xi (1, 2… SN) is a D dimensional vector where D is optimization parameters number. After initialization, the positions (solutions) population is subject to repeated cycles, C = 1, 2… MCN, of search processes of employed, onlooker and scout bees.

The pseudo-code of the ABC algorithm:

1: Initialize the population of solutions xi, i = 1... SN

2: Evaluate the population xi, Gi, i = 1, ..., NP

3: For cycle = 1 to MCN do

4: Produce new solutions vi for the employed bees and evaluate them.

5: Apply the greedy selection process.

6: Calculate the probability values pi for the solutions xi

7: Produce the new solutions vi for the onlookers from the solutions xi selected depending on pi and evaluate them.

8: Apply the greedy selection process.

9: Determine the abandoned solution for the scout, if exist and replace it with a new randomly produced solution xi

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10: Memorize the best solution achieved so far.

11: Cycle = cycle + 1

12: End for

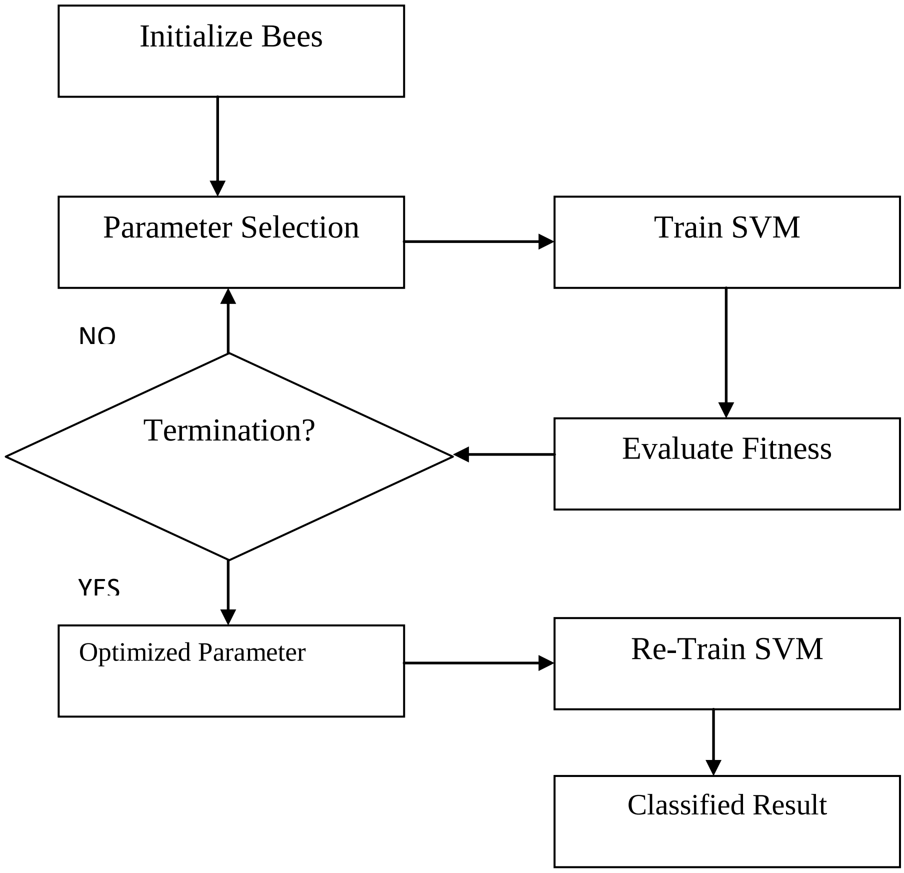


**Fig 5.1 ABC optimized SVM Classification**

To optimize the parameters C and γ, ABC is adapted to execute the search for optimal combination of (C, γ). The objective function is based on Root Mean Squared Error (RMSE) attained by the SVM-RBF. Thus, the ABC discovers the combination of (C, γ) with the lowest RMSE to optimize the performance. Figure 5.1 shows the steps involved in the proposed methodology.

## VI. EXPERIMENTS

### Dataset

We created a set of video sequences of street scenes with all pedestrians marked with a box in each frame. We have eight such sequences, each containing around 2000 frames. One frame of each sequence used for training along with the manually marked boxes. Figure 6.1 shows the example sequence of dataset images.

Figure 6.1 Training Samples

## VII. RESULTS

Tests were performed in an Intel Core i7 at 3.8 Ghz with 8 Gb of RAM. They were restricted to one execution thread because preconfigured classifiers on LibSVM are implemented under a single execution thread. The performance metrics are calculated by using the confusion matrix. Based on the matrix, accuracy, Precision, and Recall are calculated and compared with the literature method ICA.

## VIII. PRECISION

Precision (P) is the proportion of the predicted positive cases that were correct, as calculated using the equation:
Precision = True positive /(True Positive + False Positive)

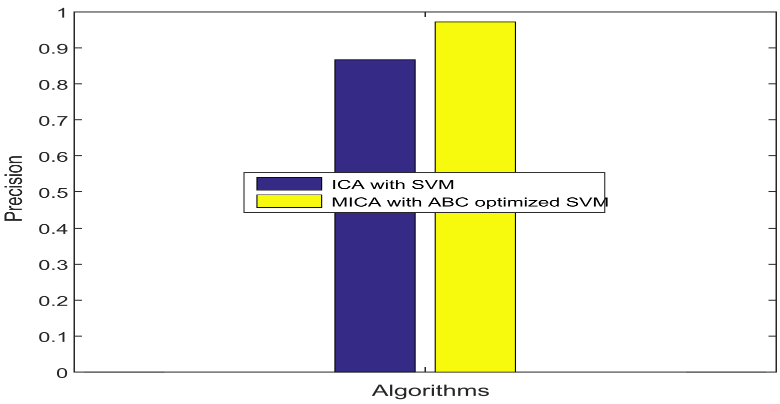


**Figure 7.1 Precision Comparison**

## IX. RECALL

The recall is the proportion of positive cases that were correctly identified, as calculated using the equation:
Recall = True positive /(True Positive + False Negative)

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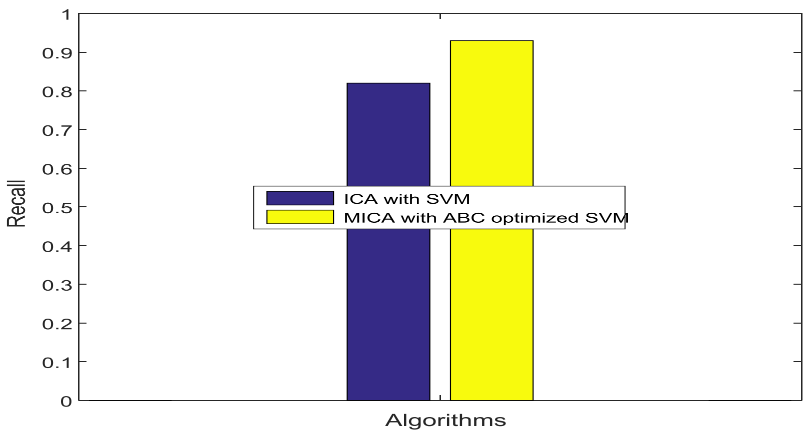


**Figure7.2 Recall Comparison**

## X.ACCURACY

The accuracy (AC) is the proportion of the total number of predictions that were correct. It is determined using the equation:

Accuracy = (TP + TN)/(TP + TN + FP + FN)

In figure, 7.1, 7.2 and 7.3 shows that, the performance of the proposed MICA with multikernel SVM acquires best accuracy, precision, recall values when compared to the literature method ICA.

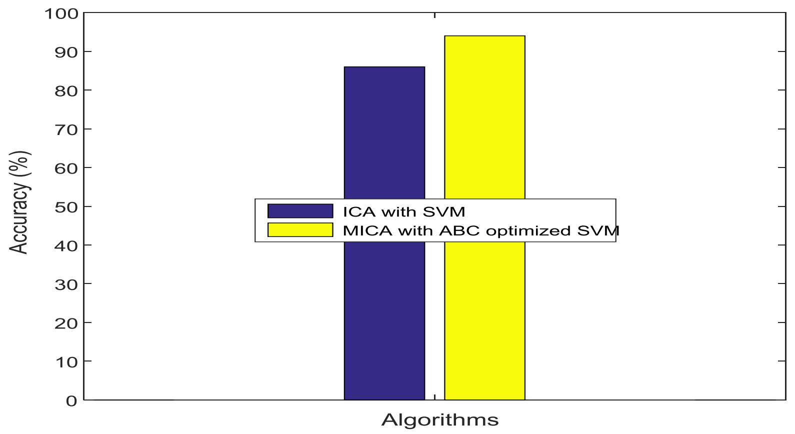


**Figure 7.3 Accuracy Comparison**

## XI. CONCLUSIONS

In this paper, we proposed an efficient pedestrian detection system using Artificial Bee colony optimized Support Vector Machine. The MICA based on eigenspace transformation is then trained using the sequence of silhouette images. Then the proposed system recognizes the human features based on ABC optimized SVM classification. The proposed system is evaluated using gait databases and the experimentation on outdoor video sequences demonstrates that the proposed algorithm achieves 94% of accuracy.

In future, we can implement the fast feature extraction algorithms so that the execution time can get decreases also can improve the recognition accuracy.

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