A Novel Fuzzy Bat Based Ambulance Detection and Traffic Counting Approach

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Abstract

In the recent years the importance of automatic traffic control has increased due to the traffic jams problem especially in big cities for signal control and efficient traffic management. The input video is processed and analyzed to detect an ambulance vehicle. This article introduces a robust approach for ambulance detection and traffic counting approach using novel fuzzy Bat swarm optimization and different image processing techniques. The fuzzy Bat based optimization algorithm is used to generate a template of ambulance from the abstracted frames obtained from predefined ambulance samples. This is done by using a collection of Gabor filters that have been particularly customized for the ambulance detection problem in which filter selection is achieved to group filters that have similar characteristics. The fitness criterion based on Support Vector Machine (SVM) is used to evaluate the output filters. The proposed approach is composed of the following five fundamental building phases: Fuzzy Bat based optimization, image acquisition, object detection, counting the connected objects, and finally ambulance detection. One of the main advantages of the proposed approach is that key Gabor filters is obtained from the selected features (filters with highest membership values) which have a vital role in the ambulance detection phase. Experimental results show that the overall accuracy confirms that the performance of the proposed approach is high.

Keywords: Ambulance detection; Gabor filters; Support Vector Machine (SVM); Swarm Intelligence; Image processing; Fuzzy logic; Computer vision.

1. Introduction

Traffic crowding has become a serious problem particularly in the big cities. The number of vehicles on the road increases daily, therefore it is important to control and manage the traffic flow to optimize the road capacity utilization [3], [4], [5], [2]. The traffic management main goal is to plan, monitor, and control traffic to guarantee a trustworthy operation of transport and good allocation of infrastructure. Also, traffic control has a good benefit of human life by playing an important role to survive [6], [7], [8].

There are different types of traffic management such as radar, infrared ray sensor, and camera. The most common method is the camera-based system because of the low cost and it is easier to maintain [9], [10], [11]. The camera-based system is less cost, easy to maintain, easy to connect through internet, can give high quality images, and provide perfect reliability and security because of the new computer technologies [1], [9]. A set of traffic information such as path changes, car-park areas, vehicle classifications etc., can be measured in such kind of systems [12].

There are lots of methods introduced to develop an automatic traffic system, for example, real time traffic density count technique is introduced in [3]. This algorithm is to determine the number of vehicles on the road by comparing the real time frame of live video by a reference image and searching in the region of interest only. In [6] another method is introduced to design a Vehicle detection and traffic assessment system, which deals with vehicle detection and classification based on different features. It uses canny edge descriptors to obtain vehicle edges. The vehicle region is extracted and subjected to feature extraction technique. The edge features and pair wise geometrical histogram are used to represent the model and type of vehicle.

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In [12] another method is introduced to design moving vehicle detection for measuring traffic count using OpenCV. The System is designed and implemented with Intel's OpenCV video stream processing system to realize the real-time automatic vehicle detection and traffic counting. Frames of live video are captured to detect moving vehicles and background is extracted from the images. The system is used to detect and classify moving vehicles such as motorcycle, light vehicles, and heavy vehicles. In [13] a controller and morphological edge detection method is introduced to measure the traffic density by comparing the live traffic image with a reference image. In [14] the Pairwise Geometrical Histograms (PGH) is used to contours matching which is not affected by rotation. The PGH which is a generalization of Chain Code Histogram (CCH)is a powerful shape descriptor. three methods are discussed: the vehicle detection using only Haar features, Haar features combined with hu moments and Haar features combined with PGH.

In [15] another method is introduced for on-road vehicle detection using a group of Gabor filters that have been particularly customized for vehicle detection problem. They optimized the Gabor filters parameters to respond stronger to features of vehicles than to non-vehicles and differentiation between the two classes. In [16] an intelligent ambulance detection system (IADS) is introduced to determine different sorts of ambulances and to output a green traffic light in the traffic jam. Their system can recognize the ambulance from different angles.

In this paper, we propose a robust traffic management system for traffic counting and ambulance detection. For this purpose, we develop a computer vision system in real time. The proposed system is composed of the following five fundamental building phases: Fuzzy Bat based optimization, image acquisition, object detection, counting the connected objects, and finally ambulance detection.

The proposed fuzzy Bat based optimization phase is comprised of the following three steps: extracting Gabor filters from ambulance samples, Fuzzy Bat based Gabor filter optimization, and generating template matrix which includes a more optimal collection of filters for ambulance detection. The object detection phase is comprised of the following six steps: pre-processing, subtracting the background, converting the image to binary, closing gaps and connecting nearby blobs, image smoothing to remove noises and very small objects, and detecting the connected objects.

The rest of this paper is represented as follows; Section 2 describes the proposed novel fuzzy bat-based ambulance detection and traffic counting system in detail; Experimental results are discussed in Section 3, followed by a conclusion in Section 4.

2. THE PROPOSED TRAFFIC COUNTING APPROACH

The proposed novel fuzzy Bat based ambulance detection and traffic counting approach is comprised of the following five fundamental building phases: Fuzzy Bat based optimization, image acquisition, object detection, counting the connected objects, and finally ambulance detection.

(1) Fuzzy Bat based optimization phase: This phase is comprised of the following three steps: extracting Gabor filters from ambulance samples, Fuzzy Bat based Gabor filter optimization, and generating template matrix which includes a more optimal collection of filters for ambulance detection.
(a) Extracting Gabor filters step: Gabor filters are considered as local bandpass filters, in which each filter is determined by four parameters in Φ. In this step the two dimensional Gabor filter g(x,y) and its Fourier transform G(u,v) are obtained to design filters for each predefined ambulance vehicle.

2.1 A brief review of Gabor filters

The optimal joint localization in spatial and frequency domains is considered as one of the most important characteristics of Gabor filters. They can be applied to different image processing and analysis applications, such as face recognition, texture analysis, vehicle detection, handwritten number recognition, and texture analysis [15], [17], [18], [19]. The two-dimensional Gabor filter function g (x, y) can be represented as a modified Gaussian function by using a complex sinusoidal signal as follows:

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} exp[-\frac{1}{2}(\frac{x'^2}{\sigma_x^2} + \frac{y'^2}{\sigma_y^2}) exp[2\pi jWx'] \quad (1)$$

$$x' = xcos\theta + ysin\theta \quad (2)$$

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$$y' = -x sin\theta + y cos\theta \quad (3)$$

where σx and σy are the filter scaling parameters. Also, they determine the pixel neighborhood size where the weighted summation occurs and θ determines the Gabor filter orientation [15]. The Fourier transform of the Gabor function is formulated as:

$$G(u,v) = exp[-\frac{1}{2}(\frac{(\mu - W)^2}{\sigma_\mu^2} + \frac{v^2}{\sigma_v^2})] \quad (4)$$

Where:

$$\sigma_\mu = \frac{1}{2}\pi\sigma_x, \sigma_v = \frac{1}{2}\pi\sigma_y.$$

(b) Fuzzy Bat based Gabor filter optimization step: In this step, a fuzzy Bat based Gabor filter optimization is employed to select the optimal features from the Gabor filter feature vector extracted from the sample images. The Gabor filter feature vector is a column vector containing the Gabor features of the image. The values of the feature vectors are normalized to zero mean and unit variance [20]. The feature vector length = (m * n * u * v)/ (dw1 * dw2). Where m is number of rows, n is number of columns, u is the number of scales, and v is the number of orientations in the 2D Gabor array. dw1 is the factor of down sampling along rows and dw2 is the factor of down sampling along columns [20].

2.2 A brief review of Bat algorithm

Bat algorithm is a global optimization metaheuristic algorithm. It was inspired by the echolocation behavior of microbats. Echolocation can be considered as a sort of sonar with varying pulse rates of emission and loudness [21]. Micro-bats emit a short sound pulse which strikes into an object, then the echo returns to their ears [21]. At that time bats can compute the distance from the object [22]. Also, bats can differentiate between a prey and an obstacle. Therefore, they can hunt even in darkness [21]. Algorithm 1 presents the Bat Algorithm (adapted from [21]).

Algorithm 1 Bat algorithm

```
Initialize Bat population x_i, for i = 1,2,...,N
Define frequency of pulse fr_i at x_i, ∀i = 1,2,...N.
Initialize rates of pulse r_i, ν_i, and loudness A_i.
repeat
  for each Bat Ba_i do
    Generate new solutions of x_i.
    if rand(0,1)> r_i then
      Choose a solution from the best solutions.
      Generate a solution a round the best solution x_best
    end if
    if rand(0,1)< A_i and fr(x_i) < fr(x_best) then
      Accept the new solutions.
      Increase r_i
      Reduce A_i
    end if
  end for
until number of iterations T = Total is reached
Order the bats and find the current best x_best
```

A bat Bai is flying randomly to find the prey. At position xi, its velocity vi, with a fixed frequency frmin, loudness A0, and varying wavelength λ. It can modify the frequency and wavelength of the pulses and modify pulse emission rate r[0, 1], depending on the nearness of the prey [21]. The velocity and position are updated during the bat movements using the following equations:

$$fr_i = fr_{min} + (fr_{min} - fr_{max})\beta \quad (5)$$

$$v_i(t) = v_i(t-1) + [xbest - x_i(t-1)]fr_i \quad (6)$$

$$x_i(t) = x_i(t-1) + v_i(t) \quad (7)$$

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Where xi(t) is the position of Bai at time t and β is a randomly generated number ∈ [0,1]. The loudness can be selected between A_{min} and $A_{max.}$ If A_{min} = 0 then the bat has just found the prey and stop emitting sounds [23]. The loudness is updated as follows:

$$A_i(t) = \alpha A_i(t) \quad (8)$$

$$r_i(t + 1) = r_i(0)[1 - \exp(-\gamma t)] \quad (9)$$

Where α and γ are constants. Firstly Ai (0) and ri (0) are generated randomly. Where Ai(0) ∈ [1,5] and ri(0) ∈ [0,1] [21]. In this paper, we have used α and γ from 0.8 to 0.99. In [21] a binary version of Bat Algorithm is proposed, in which the new bats position has only binary values using the next function:

$$x_i = \begin{cases} 1 & \text{if } \frac{1}{1+e^{-\nu_i}} > \sigma \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

The proposed fuzzy Bat based Gabor filter optimization algorithm

In this paper propose a novel fuzzy Bat version to optimize a methodology to select the best Gabor filters extracted from ambulance samples. Two fuzzy sets are constructed to optimize the solutions. The first fuzzy set OS contains the optimal solutions in which item i^{OS} belongs to the universe and μ^{OS}, is its grade of membership in OS. Where OS = {(1^{OS}, μ^{OS}), .., (N^{OS}, μ^{OS}))}.

The second fuzzy set fuzzy set NOS contains the none optimal solutions in which item i^{NOS} belongs to the universe and μ^{NOS}, is its grade of membership in NOS. Where NOS = {(1^{NOS}, μ^{NOS}), .., (N^{NOS}, μ^{NOS}))}.

The proposed fuzzy Bat algorithm is comprised of the following steps: 1- Firstly, each fuzzy set is initialized by randomly selected populations and all membership values are initialized by 1. Each fuzzy set will be modified according to the fitness during iterations. The Gabor filters are used as training input sets, by which labelled as training input sets, by which labelled training TR and evaluating EV sets are initialized. Also, the population size N, number of Bats N, number of iterations T, pulse emission r, loudness A, and α and γ values have been chosen. TR^{OS} and EV^{OS} are constructed from TR and EV (randomly selected in the first step), such that both contains filters in Ba_i where i^{OS} = GaborFilterIndex , ∀i = 1, ..., N. The rest of Gabor filters are considered as non-optimal solutions. Their membership values are set to 1 (μ^{OS} = 1). 2- Secondly, the SVM classifier is trained using TR^{OS} and EV^{OS} for evaluation and the accuracy stored in ACC. The membership values in the optimal fuzzy set are updated, where μ^{OS} = ACC for all memberships.

3- Thirdly, a randomly selected items (number of selected items=n) from the optimal fuzzy set are replaced by others selected from the non-optimal fuzzy set (where μ_i^{NOS} = 1). The new membership values of new items moved into the optimal fuzzy set are set to ACC (μ_{newi}^{OS} = ACC). The new membership values of new items moved into the non-optimal fuzzy set are set to 1 − ACC (μ_{newi}^{NOS} = 1 − ACC).

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Algorithm 2 Initialization algorithm

```
for each Bat Ba_i ∀i = 1, ...., N do
    Select random Gabor filter indices of size N
    Initialize i^OS with random Gabor filter indices, μ_i^OS = 1
end for
Construct the optimal fuzzy set OS = {(1^OS, μ_1^OS), ..., (N^OS, μ_N^OS)}
for k=1 to number of the remaining Gabor filters NR do
    Initialize k^NOS with the remaining Gabor filter indices, μ_k^NOS = 1
end for
Construct the non optimal fuzzy set NOS = {(1^NOS, μ_1^NOS), ..., (NR^NOS, μ_NR^NOS)}
Choose ν_i = 0, A_i=Random{1,5}, r_i=Random{0,1}, fitness_i = 0, lastfitness = 0, T = 500, α = 0.9,
    γ = 0.9, fr_min = 0, fr_max = 2
```

4- Fourthly, step 2 is repeated and for evaluation and the new accuracy is compared with the old one. If it is higher then, compute the difference between the new and old accuracy, store it in , store the new accuracy in ACC, update all membership values in the fuzzy optimal set OS to the new accuracy value and update the new membership values of new items moved into the optimal fuzzy set to be:

$\mu^{OS}_{new_i} = \epsilon + ACC$ and if $\mu^{OS}_{new_i} > 1$ then $\mu^{OS}_{new_i} = 1$.

If $\frac{1}{1+e^{-x_i^{OS}}} < \sigma$ then the item i^{OS} is moved from the optimal fuzzy set OS to the non-optimal fuzzy set NOS. The new membership values of new items moved into the non-optimal fuzzy set are set to $1 - ACC$ ($\mu^{NOS}_{new_i} = 1 - ACC$). 5- In this step, step 3 is repeated during iterations through the proposed Bat algorithm. The output of the algorithm is the subset of Gabor filters whose positions in the optimal fuzzy set OS. The algorithm in detail is shown in algorithm 3. The main advantage of this algorithm is that we obtain key filters which have maximum membership values ordered in the template matrix. These key filters are the most important filters in ambulance detection. (c) generating template matrix step: The constructed Template Matrix contains the selected Gabor features, their membership values, and the parameters in Φ set, such as the filter scaling parameters σ_X and σ_Y and the Gabor filter orientation θ. Image acquisition phase: We have to put a camera on a pole in this phase looking down on the traffic, connecting the camera to our system, and capturing the real time frame of live video, (3) Object detection phase: the object detection phase is comprised of six steps: pre-processing step, in which Gaussian high pass filter method is employed to illustrate the objects by sharpening the edges in such frame, background subtraction or foreground detection which is a vital step because foreground objects or regions of interest have to be determined, converting the image to binary to have only two possible values of ones and zeros for each pixel is the third step, the fourth step includes closing gaps, connecting nearby blobs, making shapes convex and filling holes, image smoothing to remove noises by Gaussian low pass filter smoothing technique is the fifth step, and the final step includes detecting the connected objects using Connected component labeling algorithm, and (4) Counting the connected objects and detecting the ambulance phase: The last phase is counting the connected objects to count number of vehicles on the road and detecting the ambulance vehicle. The overall architecture of the introduced approach is described in Figure 1.

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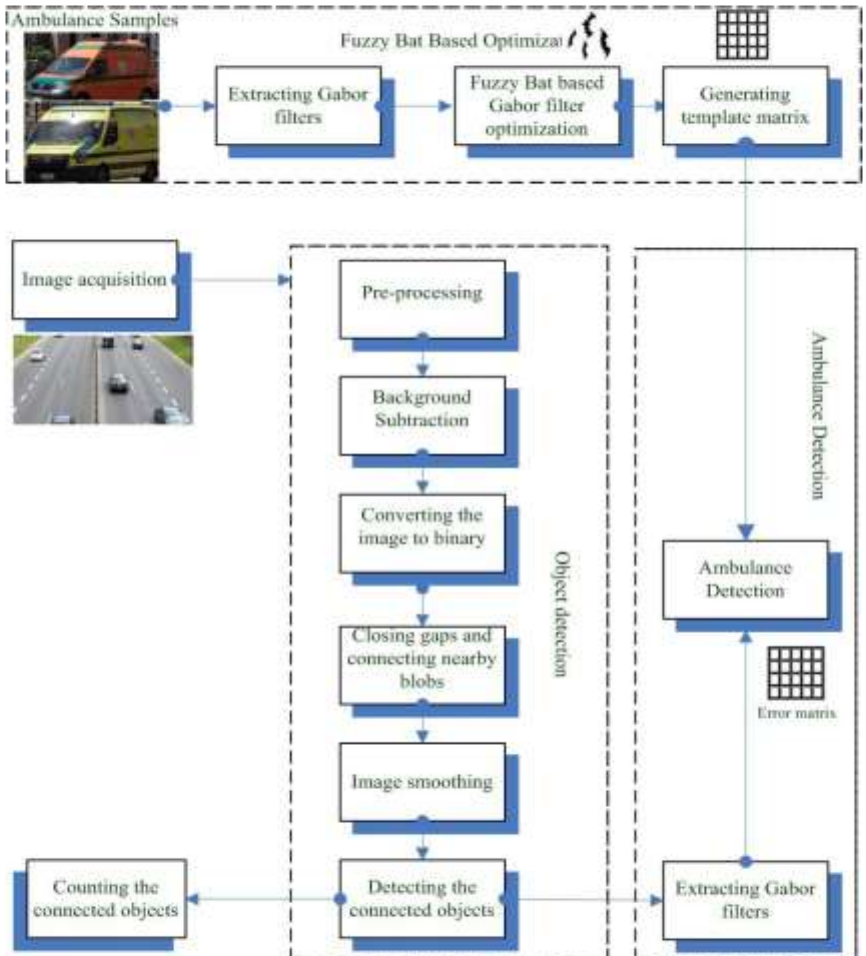

Figure 1. Bat Based Ambulance Detection and Traffic counting architecture

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Algorithm 3 Fuzzy Bat based Gabor filter optimization algorithm

Call the Initialization algorithm

for each iteration t $\forall t = 1, ..., T$ **do**

  for each Bat Ba_i $\forall i = 1, ..., N$ **do**

    Construct TR^{OS} and EV^{OS}, containing filters in Ba_i

    Train SVM classifier using TR^{OS} and use EV^{OS} for evaluation and Store the accuracy in ACC

    if $fitness_i < ACC$ **then**

      $A_i = \alpha A_i$, $fitness_i = ACC$, $r_i = r_i(0)[1 - exp(-\gamma t)]$

    end if

    $maxfitness = max(fitness_i)$, $maxindex = index(maxfitness)$

    if $lastfitness < maxfitness$ **then**

      $lastfitness = maxfitness$

      for each Gabor filter feature in the optimal fuzzy set OS **do**

        $x_{best}^{OS} = x_{maxindex}$

      end for

    end if

    if there are items that have membership $\mu_i^{NOS} = 1$ **then**

      Select randomly items of size n in OS and replace them with others selected from NOS

    else

      Select items that have minimum membership values from NOS

    end if

    $\mu_i^{OS} = maxfitness$, $\epsilon = maxfitness - lastfitness$

    $\mu_{new_i}^{OS} = maxfitness + \epsilon$,

    for each Bat Ba_i $\forall i = 1, ..., N$ **do**

      for each each item in OS i $\forall i = 1, ..., N$ **do**

        $x_i^{OS} = x_i^{OS} + \epsilon AverageLoudnessOfBats$

      end for

    end for

    if $fitness_i < lastfitness$ **then**

      for each item in OS i $\forall i = 1, ..., N$ **do**

        Apply equations 5, 6, and 7 to have the new x_i^{OS}

        if $\frac{1}{1+e^{-x_i^{OS}}} < \sigma$ **then**

          Move i^{OS} from OS to NOS, $\mu_{new_i}^{NOS} = 1 - maxfitness$

        end if

      end for

    end if

  end for

end for

for each item in OS i $\forall i = 1, ..., N$ **do**

  $SelectedGaborFeature_i = x_{best(i)}$

end for

Store the $SelectedGaborFeatures$, their membership values μ_i^{OS}, and their parameters in $TemplateMatrix$

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A. image acquisition phase

Image acquisition phase is the first phase in the workflow sequence of any computer vision system. Different methods of processing can be applied, after the image has been obtained. We put a camera on a pole in this phase looking down on the traffic scene with multiple orientations, after that the best orientation is chose to capture the live video real time frame.

B. Object detection phase

The object detection phase is comprised of six steps: (**1) Pre-processing:** In this step, Gaussian high pass filter method is employed to illustrate the objects by sharpening the edges. There are lots of tasks in image processing that can be implemented using different filters. A high pass filter is a filter that reduces frequencies lower down its crossing frequency; do not affect high frequencies to sharpen the edges. A Gaussian high pass filter of crossing frequency D_0 is defined as:

$$H(u, v) = 1 - e^{-D\ (u,v)/2D.} \qquad (11)$$

where H(u, v) is the filter Fourier transform value and D(u, v) is the distance between the point (u,v) and the center of the frequency rectangle**. (2)** Background subtraction in image processing and computer vision, is a technique by which image's foreground is extracted for processing. Background subtraction is mostly achieved if the target object is a part of a video stream frame. This step is carried out by using Mixture of Gaussians model [24], in which Mixture of K Gaussians such as μi ,σi , and ωi is applied. At every new frame, some of the Gaussians match the new value at a distance ¡ 2.5 σi and weights ωi are normalized, furthermore μi,σi are modified by the average of running . All distributions are sorted according to their ωi/σi and the first ones chosen as background. The pixel latest history, X_1, ..., X_t, is used by a mixture of K Gaussian distributions [24]. The probability of observing of new pixel value is:

$$P(X_t) = \sum_{i=1}^{K} \omega_{i,t} * \eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \qquad (12)$$

where K is the number of distributions, $\omega_{i,t}$ is the weight at time t of the i_{th} Gaussian in the mixture, $\mu_{i,t}$ is the value of mean at time t of the i_{th} Gaussian in the mixture , $\Sigma_{i,t}$ is the covariance matrix at time t of the i_{th} Gaussian in the mixture , and the Gaussian probability density function is η.

$$\eta(X_t, \mu, \Sigma) = \frac{1}{(2\pi)^{\frac{n}{2}}|\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(X_t-\mu_t)^T\Sigma^{-1}(X_t-\mu_t)} \quad (13)$$

(3) Converting the image to binary: In this step, the input image pixels are replaced with intensity less than level with the value 0 and replaces other pixels with the value 1. **(4) Closing gaps and connecting nearby blobs:** In mathematical morphology, closing and opening are important operators. Opening and closing can be considered some of the main operations of morphological noise elimination. Opening eliminates small objects, while closing eliminates small holes. Closing can be obtained from the operations of erosion and dilation. It is usually applied to binary and gray level images. Closing tends to enlarge the boundaries of foreground regions and shrink background color holes. The morphological operators are determined by a structuring element and the main task of the operator is to preserve background regions that have a similar shape to this structuring element, then removing all other regions in the background. In computational geometry, computing the convex hull of a finite set of points, with differnt computational complexities have many applications in mathematics and computer science. We used Matlab functions to Compute the convex hull to represent and construct a required convex shape.

(5) Smoothing steps Gaussian low pass filter method is employed in this step to eliminate small objects and noises. A low pass filter is used to reduces high frequencies for smoothing. A Gaussian low pass filter of crossing frequency D_0 is defined as:

$$H(u, v) = e^{-D\ (u,v)/2D_0} \qquad (14)$$

(6) Connected objects detection: The connected component labeling technique is employed to detect the connected objects. In the output images each object is labeled. Points belonging to a surface are projected to spatially closed points. It works by scanning the image from top to bottom and left to right, then assigns labels to each pixel until the labels for the pixels no longer change.

C. Counting the connected objects and ambulance detection phase

The final phase of the proposed approach is comprised of two steps: (1) Connected objects counting: to count the connected objects. It is a very easy task because each object has a different label. The number of vehicles is the number of connected objects. (2) Ambulance detection: In this step a similarity measure that quantifies the similarity between two objects is used to detect the ambulance. For each detected object, the similarity measures between each Gabor filter and Gabor filter parameters extracted from the detected object (extracted from the input image) and those in Template

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Matrix (particularly the key filters that have highest membership values) are calculated using Euclidean distance algorithm, then storing the results in an error matrix. Finally, a predefined threshold is used to detect the ambulance.

3. EXPERIMENTAL RESULTS

The figures below display the experimental results of the approach. Figure 2 shows magnitudes of Gabor filters of ambulance sample. Figure 3 shows real parts of Gabor filters of ambulance sample.

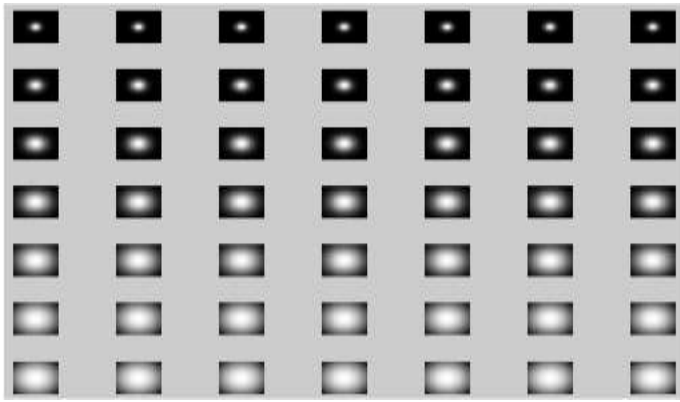

Figure 2. Magnitudes of Gabor filters of ambulance sample

Figure 4 displays a sample of input image. Figure 5 displays the resulting difference image after background subtraction. Figure 6 displays the resulting binary image. Figure 7 displays the color-labeled resulting objects. Figure 8 shows the output binary image without using pre-processing step. Here we notice that new fake objects have appeared. Figure 9 shows the color-labeled objects without using pre-processing step. Here we notice that the number of objects has been changed and there are also some shape changes. Therefore, it is less accurate than with the pre-processing step. Figure 10 shows the output binary image without using image smoothing step. Here we notice that new noises and fake objects have appeared. Figure 11 shows the color-labeled objects without using image smoothing step. Here we notice that the number of objects has been changed. Therefore, it is less accurate than with the image smoothing step. Figure 12 shows a different input image sample at night on different road. Figure 13 shows the color-labeled objects using pre-processing step. Figure 14 shows the detected ambulance object. Table 1 shows samples of Gabor filter parameters in Φ set in frequency domain.

Table 2 depicts classification accuracy using different clas- sifiers such as SVM, Multilayer Perceptron NN, BFtree, ADtree and Naive Bayes classifiers. As presented in Table 2 the classification accuracy using the SVM was 96%, Multi- layer Perceptron NN was 95%, using ADtree was 84%, and using Naive Bayes was 79%.

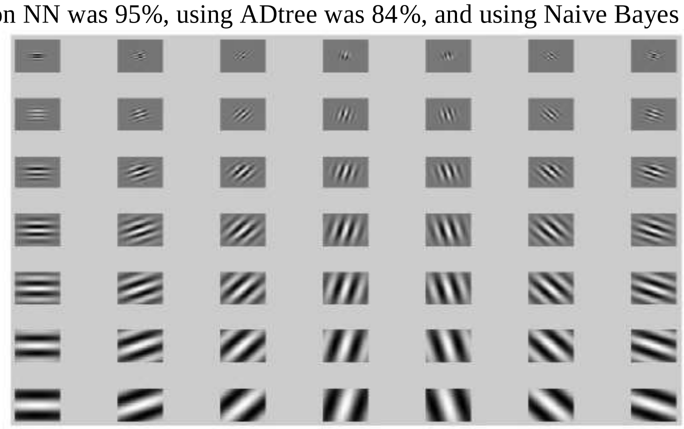

Figure 3. Real parts of Gabor filters of ambulance sample

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Figure. 4. Input sample image 1

Figure 5. The difference image

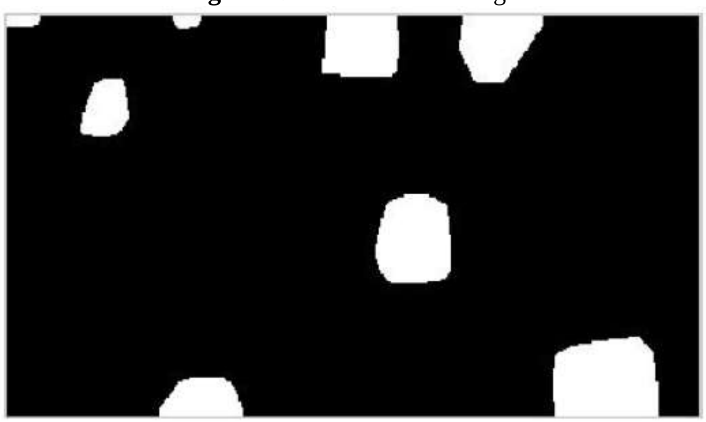

Figure 6. The output binary image

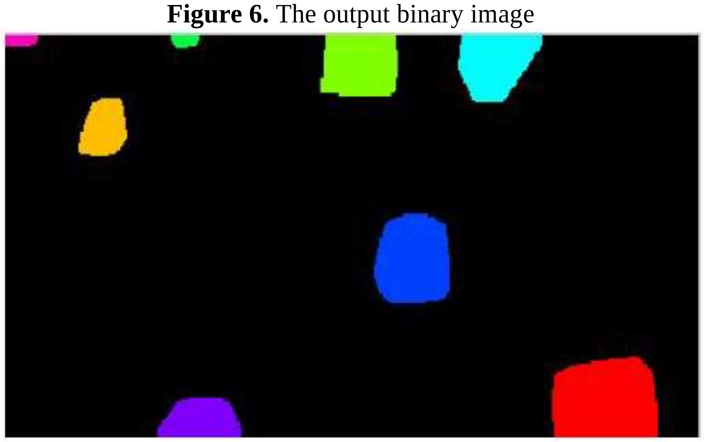

Figure 7. The color-labeled objects

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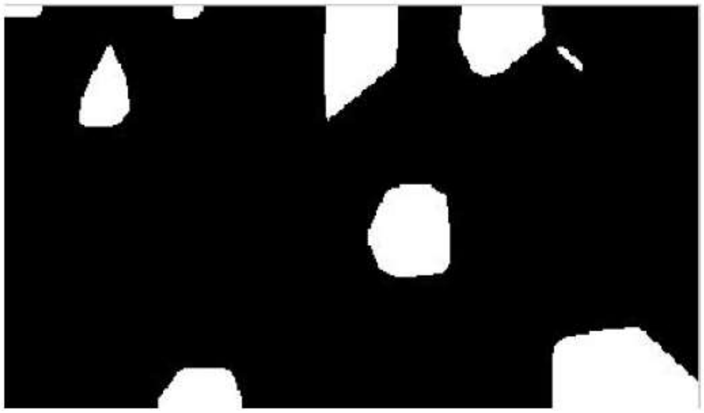

Figure 8. The output binary image without using pre-processing step

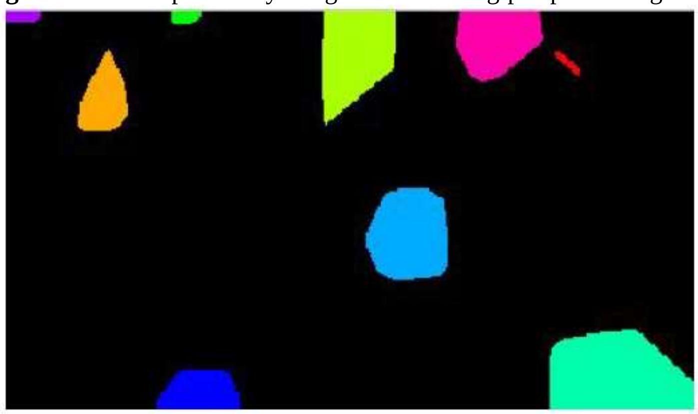

Figure 9. The output color-labeled objects without using pre-processing step

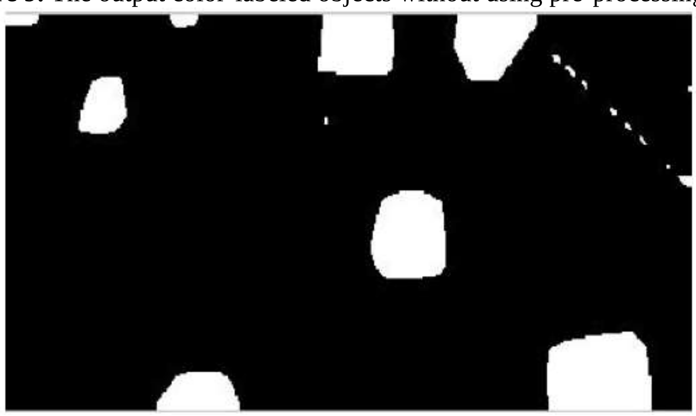

Figure 10. The output binary image without using image smoothing step

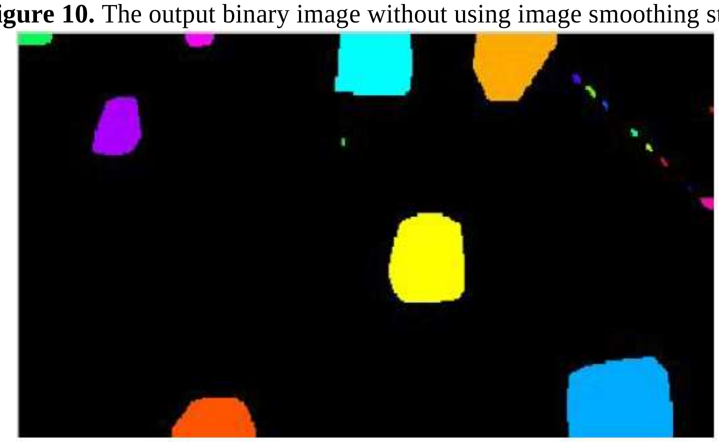

Figure 11. The output color-labeled objects without using image smoothing step

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Figure 12. Input sample image 2 at night on different road

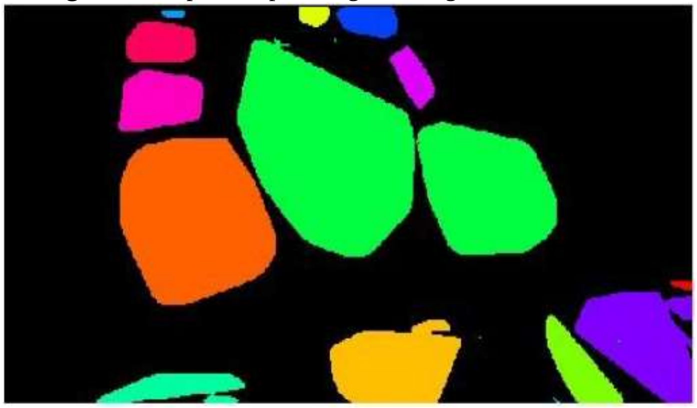

Figure 13. The color-labeled objects using pre-processing step

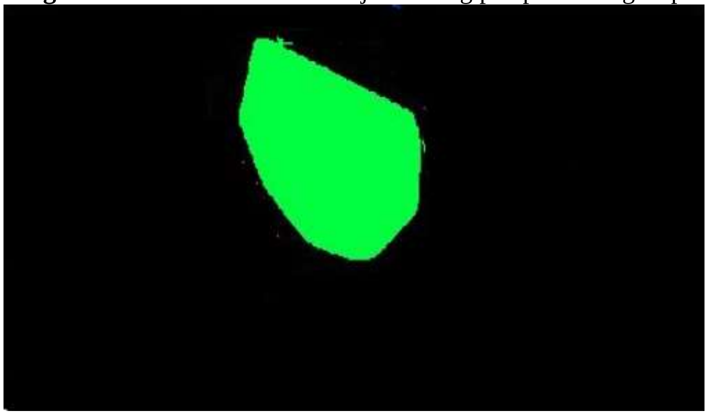

Figure 14. The color-labeled detected ambulance object

Table 1. Samples of gabor filter parameters in Φ set

θ	W	σ_x	σ_y
0	0.079	0.030	0.020
0	0.044	0.050	0.443
90	0.3900	0.0.701	0.412
90	0.299	0.0.606	0.454

Table 2. Classification results: accuracy, mean absolute error (MAE), root mean squared error (RMSE), and relative absolute error(RAE)

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Classifier	Accuracy	MAE	RMSE	RAE
SVM	96 %	0.0439	0.1523	8.644 %
Multilayer Perceptron NN	95 %	0.099	0.345	20.9 %
ADtree	84%	0.336	0.432	59.8000 %
Naive Bayes	79%	0.344	0.599	68.222 %

4. CONCLUSIONS

This paper introduces a real-Time novel fuzzy Bat based ambulance detection and traffic counting method on the road by using optimization and image processing algorithms. One of the major advantages of the proposed method is that key Gabor filters is obtained from the selected features (filters with highest membership values) ordered in the template matrix which have a vital role in the ambulance detection phase. No need to use complex sensor-based systems is another important advantage of the proposed method. The proposed method is cost effective because we do not need additional expensive devices. These key filters are the most important filters in ambulance detection. The experimental results obtained, show that the overall accuracy offered by the employed proposed techniques is optimized and high.

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