

# An Improved “Flies” Method for Stereo Vision: Application to Pedestrian Detection

Hao LI, Gwenaelle TOULMINET, Fawzi NASHASHIBI

**ABSTRACT** — In the vast research field of intelligent transportation systems, the problem of detection (and recognition) of environment objects, for example pedestrians and vehicles, is indispensable but challenging. The research work presented in this paper is devoted to stereo-vision based method with pedestrian detection as its application (a sub-part of the French national project “LOVe”: Logiciels d’Observation des Vulnerables). With a prospect of benefiting from an innovative method i.e. the genetic evolutionary “flies” method proposed by former researchers on continuous data updating and asynchronous data reading, we have carried on the “flies” method through the task of pedestrian detection affiliated with the “LOVe” project. Compared with former work of the “flies” method, two main contributions have been incorporated into the architecture of the “flies” method: first, an improved fitness function has been proposed instead of the original one; second, a technique coined “concentrating” has been integrated into the evolution procedure. The improved “flies” method is used to offer range information of possible objects in the detection field. The integrate scheme of pedestrian detection is presented as well. Some experimental results are given for validating the performance improvements brought by the improved “flies” method and for validating the pedestrian detection method based on the improved “flies” method.

## I. INTRODUCTION

Research works on intelligent transportation systems have progressed rapidly around the world and have been showing more and more promising results for enhancing urban traffic safety and efficiency. The problem of detection (and recognition) of environment objects, for example pedestrians and vehicles, is indispensable but challenging. Many research works have been devoted to the problem; take pedestrian detection as an example, mono-vision based methods have been introduced in [1][2] while laser-scanner based methods in [3]. Experiences show that methods based on single on-vehicle sensor have considerable limitations due to the limited capability of the sensor itself. Therefore, the fusion strategy among multiple on-vehicle sensors has been exploited to achieve either faster computation or more

desirable detection results. The method using fusion between laser scanner and mono-camera has been discussed in [4]. The method based on stereo-vision (i.e. the fusion between two mono-cameras) has long since been researched for indoor applications [5] and has later been extended to outdoor applications as well [6][7]. The research work presented in this paper is devoted to stereo-vision based method with pedestrian detection as its application (a sub-part of the multi-participants French national project “LOVe” (Logiciels d’Observation des Vulnerables) which aims at localization of vulnerable objects, e.g. pedestrians, in a traffic scenario [8].

Stereo-vision techniques enable the process of recovering the range information of the environment from a pair of image views. This process often involves establishing correspondence between both images, either by finding corresponding pixels i.e. the so-called disparity map (dense correspondence) [7] or by finding corresponding edges (sparse correspondence) [6][9]. The methods based on edge correspondence inevitably incur the problem of edge extraction which itself is challenging and susceptible to environment conditions; while the methods based on disparity map show robust detection result but the computational demand is forbidding for real-time applications. Besides these commonly used stereo-vision techniques, Louchet et al have put forward an innovative method which they label as the “flies” method [10][11]. Instead of establishing correspondence between 2-D images, the “flies” method directly evaluate the fitness (defined in certain way) of a group of 3-D points i.e. “flies”, and use genetic evolutionary techniques to converge these flies to places with high fitness values (which correspond to real 3-D objects). With a prospect of benefiting from the “flies” method on continuous data updating and asynchronous data reading, we have carried on the “flies” method through the task of pedestrian detection affiliated with the “LOVe” project.

Compared with former work of the “flies” method, two main contributions have been incorporated into the architecture of the “flies” method: first, an improved fitness function has been proposed instead of the original one; second, a technique coined “concentrating” has been integrated into the evolution procedure. The improved “flies” method is used to offer range information of objects in the detection field (latter referred to as “OOI”, Objects Of Interest). The paper is organized as follows: The basic philosophy of the “flies” method is briefly reviewed and the limitation of the original fitness function is analyzed in section 2; An improved fitness function as well as a

Hao LI: a PhD student at the Robotics Laboratory, Mines Paris (ParisTech) / INRIA-IMARA team (B.P.105,78153 Le Chesnay France)(e-mail: hao.li@inria.fr)

Gwenaelle TOULMINET: professor assistant at INSA of Rouen and associate researcher at JRU LaRA, Mines Paris (ParisTech)(e-mail: gwenaelle.toulminet@mines-paristech.fr)

Fawzi NASHASHIBI: with the Robotics Laboratory, Mines Paris (ParisTech) and with INRIA-IMARA team (B.P.105,78153 Le Chesnay France) (e-mail: fawzi@ensmp.fr)

“concentrating” technique is proposed in section 3; The integrate scheme of pedestrian detection is described in section 4 while experimental results are presented in section 5, followed by a conclusion in section 6.

## II. THE FLIES METHOD

### A. Review of the philosophy of the flies method [11]

A fly is defined as 3-D point  $(x, y, z)$ ; its projection on the left image is denoted as  $(u_L, v_L)$  and latter referred to as “left projection” while its projection on the right image is denoted as  $(u_R, v_R)$  and referred to as “right projection”; The  $(u_L, v_L)$  and  $(u_R, v_R)$  can be easily computed from  $(x, y, z)$  with calibrated camera parameter. If a fly is situated on an opaque object, the neighborhoods of its left projection and right projection are almost identical; otherwise, there is large difference between the neighborhoods of its two projections. Based on this heuristic observation, a fitness function can be defined to evaluate the degree of similarity between the neighborhoods of a fly’s left projection and right projection. In other words, the fitness function is defined in a way that a high fitness value is generally computed for a fly on an object but a low fitness value for a fly off an object. The fitness function used in former research [11] is re-written here; see Eq.(1):

$$fitness(fly) = \frac{G}{\sum_{(i,j) \in N} (L(u_L + i, v_L + j) - R(u_R + i, v_R + j))^2} \quad (1)$$

Where the denominator means the summed square of the grey-level difference between corresponding pixels in the two neighborhoods of the fly’s left and right projections; the numerator ‘ $G$ ’ is “defined as the square root of an image gradient norm” [11].

The philosophy of the flies method is to detect environment objects by searching more and more flies with high fitness value through genetic evolution. Genetic evolution techniques are used to evolve a group of randomly initialized flies so that they may converge onto visible objects. The genetic evolution techniques [11] include 1) selection: retaining those best individuals; 2) sharing: reducing the fitness values of flies located in crowded areas; 3) mutation: adding random variances to the flies; 4) crossover: bearing new fly which is randomly located on the line segment of its parent flies. After a certain number of evolutionary iterations, the flies are expected to gather onto the surfaces of visible objects in the detection field.

### B. The limitation of the original fitness function

Consider the fitness function Eq.(1); the inverse of the denominator gives high fitness values to flies whose left and right projections have similar neighborhoods; the numerator ‘ $G$ ’, as explained in [10], is a normalizing factor that is adopted so as to reduce the fitness values of flies over insignificant regions, especially uniform regions. The fitness function Eq.(1) seems plausibly effective. However, it is

susceptible to quasi-uniform regions with small variances of high spatial frequencies.

A piece of synthetic “uniform” patch is composed for showing the limitation of Eq.(1), as shown at the left side in Fig.1 (a). There is small grey-level variance (difficult to see by naked eye) within it; the variance is indicated by a white-black alternating pattern on its immediate right side. Consider the fly ‘A’, the neighborhoods of its left and right projections are exactly the same, resulting in the denominator in Eq.(1) being zero. Although the numerator ‘ $G$ ’ is small (but non-zero), the fitness value computed via Eq.(1) is high (infinite). As a consequence, the fly ‘A’ may be mistaken as

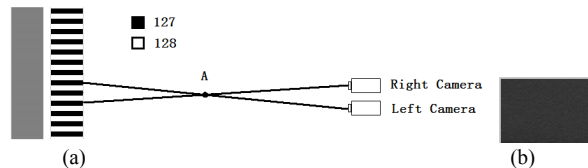


Fig.1. (a) the quasi-uniform pattern; (b) a real patch of road surface

being situated on the patch.

Above synthetic example is a bit exaggerated; in real situations, however, the problem of marking high fitness value to flies with wrong depth due to Eq.(1) still exists. This often happens where flies are in front of some quasi-uniform regions such as road surfaces; see Fig.1 (b). A simple tactic of adding a positive constant to the denominator so as to avoid it being zero does not help much.

## III. AN IMPROVED FITNESS FUNCTION AND A “CONCENTRATING” TECHNIQUE

The original flies method has been briefly reviewed and the limitation of the original fitness function has been analyzed in the previous section. In this section, we are going to propose first an improved fitness function and then a concentrating technique.

### A. The improved fitness function

Before any fitness function is constructed, it’s better to consider which features deserve high fitness value (called “desirable features”). As described in former work [11], desirable features are considered from two aspects: a) similarity and b) informativeness. “Similarity” means the similarity between the two neighborhoods of a fly’s left and right projections; the more similar the two neighborhoods are, the higher the fitness value is. “Informativeness” means the extent of variance within the neighborhoods. The more informative the neighborhoods are (like those with a lot of textures and contrasts), the higher the fitness value is. In the original fitness function Eq.(1), the “similarity” is measured by the summed square difference (SSD), i.e. the summed square of the grey-level difference between corresponding pixels in the two neighborhoods; while the “informativeness” is measured by the square root of an image gradient norm.

The limitation of the original fitness function has already been analyzed. Besides, using the SSD to measure the similarity (though it is simple and direct) between the two

neighborhoods has another limitation. Because of the limitation of camera calibration and image rectification and because of the influence of quantization process, even a fly is right on an object, the neighborhoods of its two projections still have some differences which are often likely to be increased in proportional to the extent of contrast within the neighborhoods. In other words, the more and larger the variations are there in an area, the more difficult it is for this area's projections on both images to be the same. As a result, the SSD tends to mark lower scores for informative regions than non-informative regions, which is not desirable.

The to-be-proposed fitness function is also constructed based on considerations from the two aspects "similarity" and "informativeness". Instead of the SSD which takes into account strictly the pixel-to-pixel difference between the two neighborhoods, a new fitness function based on covariance and the difference of grey-level mean is proposed, shown in Eq.(2):

$$\begin{aligned} \text{fitness}(\text{fly}) &= \sum_{j=-vSz}^{+vSz} C_j(\text{fly}) \cdot D_j(\text{fly}) \quad (2) \\ C_j(\text{fly}) &= \sum_{i=-uSz}^{+uSz} [L(u_L + i, v_L + j) - \bar{L}_j(\text{fly})] \cdot [R(u_R + i, v_R + j) - \bar{R}_j(\text{fly})] \\ D_j(\text{fly}) &= \exp(-\|\bar{L}_j(\text{fly}) - \bar{R}_j(\text{fly})\|) \\ \bar{L}_j(\text{fly}) &= \text{mean}\{L(u_L + i, v_L + j) \mid i = -uSz, \dots, +uSz\} \\ \bar{R}_j(\text{fly}) &= \text{mean}\{R(u_R + i, v_R + j) \mid i = -uSz, \dots, +uSz\} \end{aligned}$$

Where  $(u_L, v_L)$  and  $(u_R, v_R)$  are respectively the left and right projections of the fly; their neighborhoods are respectively  $L(u_L + i, v_L + j)$  (called "left neighborhood") and  $R(u_L + i, v_L + j)$  (called "right neighborhood") for  $i = -uSz, \dots, +uSz$ ;  $j = -vSz, \dots, +vSz$ ;  $L_j(\text{fly})$  is the grey-level mean of row  $j$  in the left neighborhood while  $R_j(\text{fly})$  is the grey-level mean of row  $j$  in the right neighborhood. It is worth noting that the objects concerned (pedestrians) are normally vertical for our camera configuration; thus horizontal variances are more useful than vertical variances. This is why the new fitness function is constructed in a "row-by-row" manner.

The  $C_j(\text{fly})$  is constructed in accordance with standard definition of covariance; the  $D_j(\text{fly})$  is the exponential function in terms of the absolute difference of the grey-level means of two corresponding rows. The considerations for "similarity" and "informativeness" are integrated comprehensively in the new fitness function. If the two neighborhoods have similar grey-levels on general (then  $D_j(\text{fly})$  is large) and they are informative and similar (then  $C_j(\text{fly})$  is large), a high fitness value is computed via Eq.(2). Otherwise, either  $C_j(\text{fly})$  or  $D_j(\text{fly})$  might be small, resulting in a low fitness value. More words hovering around the "similarity" aspect, the criterion of measuring similarity by the difference of grey-level mean and the covariance is a bit "loose" compared with the SSD. It is this "looseness" that gives some tolerance to the inaccuracy of camera calibration and image rectification and the influence of quantization process. The performance improvements brought by the new

fitness function are demonstrated in latter sections.

### B. The concentrating technique

After the evolution process, the result is a group of cloud-like flies which gather roughly around OOI. These fly-clouds are difficult to be used directly; a technique labeled "concentrating technique" is proposed for "concentrating" these fly-clouds (with thousands of flies) to several points which correspond to the position of OOI. The concentrating technique is incorporated into the flies method because of two reasons: first, it is used to output meaningful localization results of OOI; second, its output can be used to guide the re-generation of new fly population in the genetic evolution process. It is worth noting that a simple tactic of localize OOI by finding flies with local maximum fitness value is not practical because few flies which are far away from real objects might have high fitness value due to coincidental similarity between its backgrounds on both images.

The principle of the proposed concentrating method is to localize OOI by finding points with local maximum fitness value density. This process is similar to that of finding the modes presented in [12], where a mean-shift method is described. Here, the mean-shift method is borrowed from [12]. Besides, a step of "histogram based sampling" is used as a fast procedure to generate some sampling points which can be served as proper starting points for the mean-shift process. The proposed concentrating technique consists of two steps: 1) histogram based sampling; 2) mean-shift.

#### 1) Histogram based sampling:

Several narrow view-angles which cover the detection field are chosen. This step is to locate a sample point for each narrow view-angle chosen; the sample point is the place with largest vote of the fitness value histogram within the view-angle. For a narrow view-angle, if there is OOI inside (Fig.3 (a)), the area around OOI is likely to be the area with highest fitness value density in it (Fig.3 (b)). Therefore, the sample point of this view-angle is normally close to the OOI. Then, starting mean-shift process from the sample point will facilitate convergence to the position of OOI. The detailed procedures of "histogram based sampling" are described below in this sub-part while the mean-shift process described in the following sub-part.

- [i] Choose several narrow view-angles which cover the detection field.
- [ii] For each view-angle, compute a histogram (Fig.3 (c)) from the flies within the view angle according to the distance, i.e. the longitudinal coordinate 'x'; the vote is weighted by the fitness value of the fly.
- [iii] For each view-angle (denote its direction angle generally as  $\tan^{-1}k_i$ ), find the distance interval with the largest vote (suppose it to be  $[x_k, x_{k+1}]$ ); then the sample point of this view-angle is computed via (let all sample points be situated on the ground surface, i.e.  $z = 0$ ):
$$(x_i, y_i, z_i) = (d_i, d_i \cdot k_i, 0); d_i = (x_k + x_{k+1}) / 2;$$

#### 2) Mean-shift:

The sample points obtained from the previous step are

served as starting points for the mean-shift process described below.

[i] Imagine all the flies are temporarily situated on ground, i.e. let their ‘z’ coordinate be temporarily 0; then project all the flies onto the left image (or right image). Latter, the mean-shift process is carried out in the left image coordinate instead of directly in the world coordinates; and the bandwidth matrix can be assigned uniformly to be the identity matrix, i.e.  $\mathbf{H} = h^2\mathbf{I}$ . Otherwise, different bandwidth matrixes have to be assigned to the flies according to their depth because same pixel length means different physical length at different depth. This will not only increase the complexity of the bandwidth matrixes assignment itself but also increase computational burden.

[ii] The algorithm for mean-shift is derived from the general case introduced in [12]:

$$w_i = \frac{f(p_i) \cdot \exp(-(p_{old} - p_i)^T(p_{old} - p_i)/(2h^2))}{\sum_{k=1}^n f(p_k) \cdot \exp(-(p_{old} - p_k)^T(p_{old} - p_k)/(2h^2))}$$

$$p_{new} = \sum_{i=1}^n w_i p_i$$

Where  $\{p_i | i = 1, 2, \dots, n\}$  are the positions of all the flies on the left image;  $f(p_i)$  is the fitness value of fly  $p_i$ ;  $p_{old}$  is the old position of the sample point while  $p_{new}$  is the new position of it. For each sample point, repeat mean-shift for few times.

[iii] Cluster the sample points using a simple distance criterion; the distance threshold is chosen to be  $h$ . Compute the geometric center of each cluster, which is referred to as ‘‘candidate point’’.

[iv] Discard those candidate points with low fitness value density; fitness value density is computed via (also derived from the general case introduced in [12]):

$$d(p) = \frac{1}{n(\sqrt{2\pi}h)^{\dim}} \sum_{k=1}^n f(p_k) \cdot \exp\left(-\frac{(p - p_k)^T(p - p_k)}{2h^2}\right)$$

For simplicity, the normalizing constant can be omitted.

[v] Re-project each candidate point from the left image onto the ground surface; the positions of these candidate points in the world coordinates are regarded as the positions of OOI and are the output of the proposed concentrating technique.

#### IV. THE INTEGRATE SCHEME OF PEDESTRIAN DETECTION

The improved flies method which can offer range information of OOI has been introduced in previous sections. In combination with learning-based classifier, it has been applied to pedestrian detection as a sub-part of the French national project ‘‘LOVe’’.

The range information of OOI offered by the improved flies method can be used to extract some ROI (Region Of Interest) boxes on the image. For each box (its size is 48x96 pixels after normalization), a feature vector based on HOG (Histogram of Oriented Gradient) [13] is computed and then fed to a SVM for classification; the SVM has been pre-trained

off-line with the HOG-based feature vectors computed from 10000 pedestrian examples (normalized boxes which contain pedestrians) and 18000 non-pedestrian examples (normalized boxes which do not contain pedestrians).

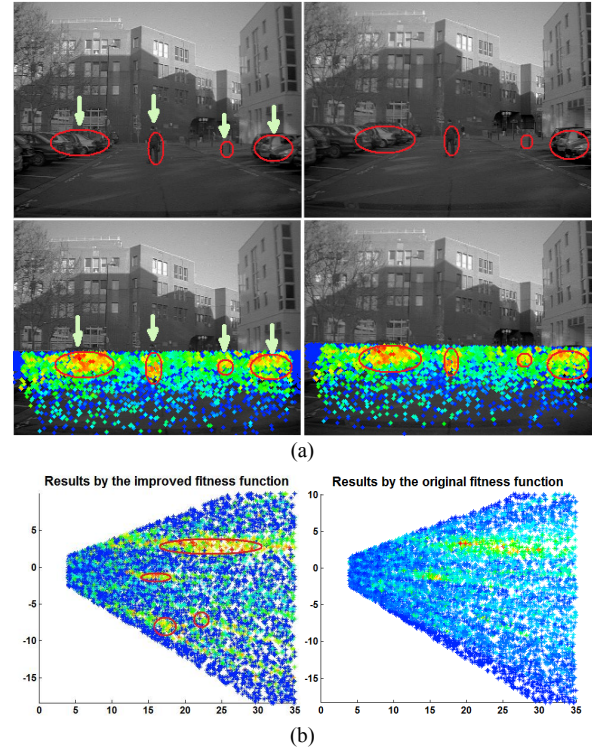


Fig.2. (a) fitness values of the flies indicated by different colors (results by the improved fitness function); (b) comparison between the performances of the improved fitness function and the original fitness function

## V. RESULTS

### A. The evaluation of the improved fitness function and comparison with the original one

3000 flies are initialized randomly in the detection field. The fitness values of the flies are computed via the improved fitness function Eq.(2). All the flies are displayed in the image coordinates (Fig.2 (a)) and in the world coordinates (the left part of Fig.2 (b), in bird-eye view); the fitness value of each fly is indicated by its color: the higher the fitness value is, the warmer the color is (the maximum and minimum fitness value are respectively indicated by pure red color and pure blue color). See areas marked by red circles, on the whole the color of flies around real objects (pedestrians, cars, poles) are apparently warmer than that of flies at non-object area. This shows that the improved fitness function is effective in distinguishing flies at object area from those at non-object area.

Fitness values are computed for the same flies via the original fitness function Eq.(1) (a constant is added to the denominator to avoid it being zero). Fitness values computed via Eq.(1) are also indicated by different colors like before;



see the right part of Fig.2 (b). Compare the left part (results by the improved fitness function) with the right part (results by the original fitness function) of Fig.2 (b); qualitatively speaking, the color differences between flies at object area and flies at non-object area are more prominent in the left part than in the right part of Fig.2 (b). In other words, the improved fitness function is more effective than the original fitness function in distinguishing flies at object area from those at non-object area.

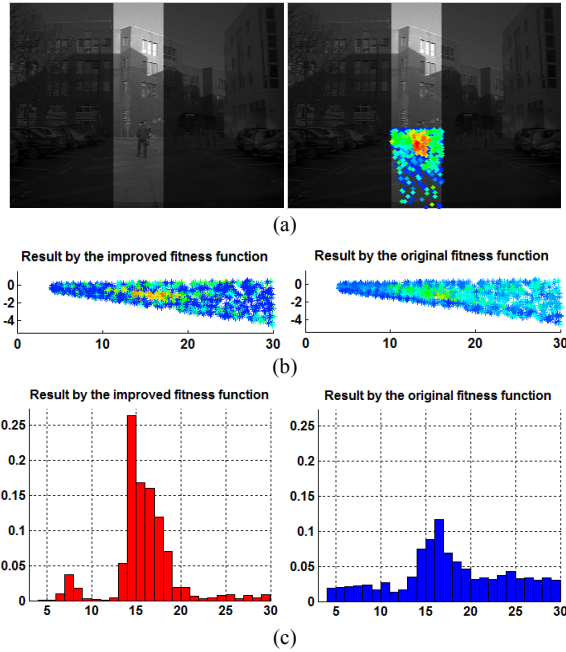


Fig.3. (a) a view-angle which contains a pedestrian; (b) fitness values of the flies indicated by different colors; (c) histograms according to distance

For quantitative comparison, a view-angle which contains a pedestrian is chosen; see Fig.3 (a). For this view-angle, compute a histogram from the flies within it according to the distance; the vote is weighted by the fitness value of the fly. First, fitness value is computed via the improved fitness function and the histogram obtained is displayed in the left part of Fig.3 (c); then fitness value is computed via the original fitness function and the histogram obtained is displayed in the right part of Fig.3 (c). The ground-truth position of the pedestrian is (15.52, -1.10, 0), i.e. 15.52 meters ahead of the vehicle. It can be seen that the votes of histogram in the left part of Fig.3 (c) are more concentrated to where the pedestrian is than in the right part of Fig.3 (c).

The root mean square distance (weighted by the fitness value of each fly) from each fly within the view-angle to the pedestrian is computed to be 2.94 meter if the improved fitness function is used while 6.86 meter if the original fitness function is used. The root mean square distance associated with the improved fitness function is noticeably smaller than that associated with the original fitness function. This quantitative result also shows that the improved fitness function is more effective than the original fitness function in

distinguishing flies at object area from those at non-object area.

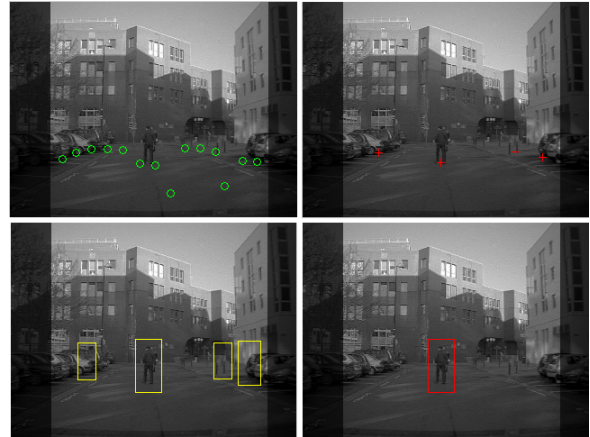


Fig.4. the process of the concentrating technique and its application to pedestrian detection

### B. The performance of the concentrating technique

The concentrating technique consists of two steps: histogram based sampling and mean-shift. See the example shown before (Fig.3), the histogram based sampling step can have a rough localization result of OOI, i.e. (14.50, -0.94, 0) which is close to the ground-truth value (15.52, -1.10, 0) and can be served as good starting point for the mean-shift step. Nevertheless, this localization result still has considerable error; thus the mean-shift step is needed to advance the localization result to more accurate one. For this example, the localization result after mean-shift is (15.43, -1.13, 0) which is much closer to the ground-truth value.

For the whole image, see Fig.4 for example. As shown in the top-left part, a group of sample points generated by the histogram sampling step are marked by green circles. Some of these sample points are close to OOI, some are not. During the mean-shift step, these sample points either converge to OOI (with high fitness value density) or converge to somewhere with low fitness value density; those sample points which converge to the latter case are discarded while others are kept. The final outputs of the mean-shift step are marked by red crosses as shown in the top-right part of Fig.4; the positions of these red crosses are consistent with the positions of OOI like the pedestrian, the cars and the poles in the environment. This shows the effectiveness of the concentrating technique in localizing OOI.

### C. Pedestrian detection

The outputs of the improved flies method are the 3D positions of several OOI, which can be used then to generate several ROI on the image; see the down-left part of Fig.4, the cars on both side, the poles on the right side and the pedestrian in the middle are detected by the improved flies method and several ROI boxes are generated around them. A HOG-based feature vector is computed for each box and then fed to a pre-trained SVM for classification; positive results are regarded as pedestrians, as shown in the down-right part of

Fig.4. More results are demonstrated in Fig.5.

#### D. Computational efficiency

The whole work is implemented in C++ in windows operating system; the CPU is 2.0GHz and the RAM is 2.0GB. The step of classification takes almost no time (<10ms) because the SVM classifier only has to deal with few ROI. The evolution part consumes most computational time which depends on the number of evolutionary iterations. It is true that more evolutionary iterations will drive flies onto more detailed 3-D structures (useful for 3-D construction) and also take more computational time. But for our application, two or three evolutionary iterations are normally enough for locating OOI, which take no more than 150ms. This computational efficiency can satisfy real-time demand.

### VI. CONCLUSION

This paper presents an improved version of the genetic evolutionary “flies” method. An improved fitness function is proposed instead of the original one; a concentrating technique is incorporated into the architecture of the flies method. Experimental results are given for validating the improved performance brought by the proposed fitness function and for showing the effectiveness of the improved flies method in localizing OOI. In combination with a SVM classifier, the improved flies method is applied to pedestrian detection as a sub-part of the French national project “LOVe”.

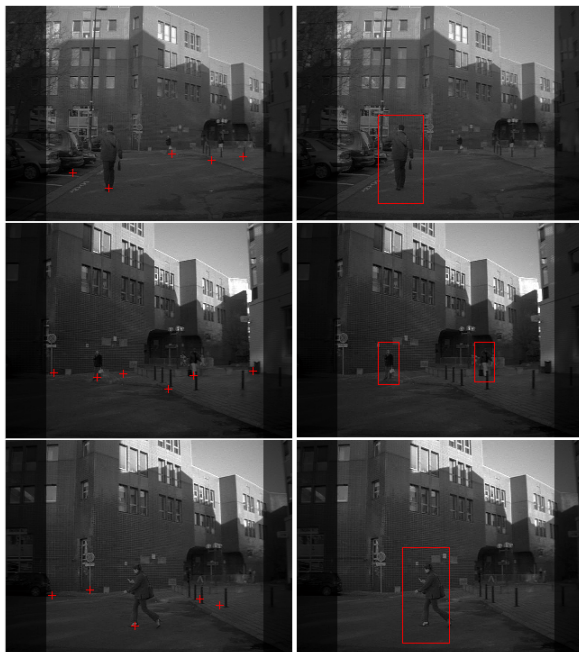


Fig.5. pedestrian detection

The strategy of using the fusion between camera and laser scanner for pedestrian detection has been showing promising results [4]. One merit of this strategy is that the laser scanner can be used to offer reliable localization results of OOI and reliable ROI on the image. The improved flies method presented in this paper, if considered from its function,

can be regarded as a laser scanner, while the device (stereo-vision) needed for it is considerably cheaper than a laser scanner. On the other hand, there are still spaces for improvements. By so far, size information of OOI located can not be offered; besides, occasionally few objects in the detection field will be missed, without being detected as OOI. To be able to offer size information of OOI and to reduce the rate of relevant objects undetected are the direction for further research.

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