METU

Electrical and Electronics Engineering Department

EE 553

2021-2022 Fall Term

Project Report:

Infrared Small Target Detection Based on the Dynamic Particle Swarm Optimization

Student Name: Onur Selim KILIÇ

Student Number: 2169530

Name: Onur Selim KILIÇ
Student Number: 2169530
10 February 2022

TABLE OF CONTENTS

TABLE OF FIGURES

Name: Onur Selim KILIÇ
Student Number: 2169530
10 February 2022

1. Introduction

Infrared search and tracking (IRST) systems are among the most essential tools in the military industry. These systems use infrared radiation to detect targets. Therefore, they can protect unwanted interferences. In my project, I have implemented a new infrared small-target detection algorithm is introduced based on the particle swarm optimization (PSO) algorithm. This algorithm is a Dynamic-PSO implemented according to the specific conditions of infrared small-target detection. This method is called the Dynamic Particle Swarm Detector (DPSD).

The codes of my implementation together which also includes the instructions can be found in the zip file.

2. Methodology

2.1. Particle Swarm Optimization

Particle swarm optimization (PSO) was first introduced in 1995. This technique has been used in several optimizations and engineering problems. The original idea of the search method in this algorithm came from the regular movement of birds and fishes. To model the existing order in the massive movement of these creatures, there are two perspectives involved, one referring to the social interactions among group members and the other to individual features. The former entails all group members' commitment to change their position according to that of the best member and the latter involves each member's tendency to the best position experienced personally in the past. In this algorithm, the position and speed of each particle is stated in the following relation:

$$\mathrm{v}_{\mathrm{i}}^{\mathrm{d}}(\mathrm{t}+1) = \mathrm{W} \times \mathrm{v}_{\mathrm{i}}^{\mathrm{d}}(\mathrm{t}) + \mathrm{rand} \times \alpha \times \mathrm{c}_1 \times ({\mathrm{p}_{\mathrm{best}_\mathrm{i}}}^{\mathrm{d}} - \mathrm{x}_{\mathrm{i}}^{\mathrm{d}}(\mathrm{t})) + \mathrm{rand} \times (1-\alpha) \times \mathrm{c}_1 \times ({\mathrm{E}_{\mathrm{best}}}^{\mathrm{d}} - \mathrm{x}_{\mathrm{i}}^{\mathrm{d}}(\mathrm{t})) + \mathrm{rand} \times \mathrm{c}_2 \times ({\mathrm{G}_{\mathrm{best}}}^{\mathrm{d}} - \mathrm{x}_{\mathrm{i}}^{\mathrm{d}}(\mathrm{t}))$$

$$\alpha = \begin{cases} \dfrac{\#Iteration}{Max\_Iteration} if \#Iteration < Max\_Iteration \\ 1 if \#Iteration > Max\_Iteration \end{cases}$$

$$\mathrm{x}_{\mathrm{i}}^{\mathrm{d}}(\mathrm{t}+1) = \mathrm{v}_{\mathrm{i}}^{\mathrm{d}}(\mathrm{t}+1) + \mathrm{x}_{\mathrm{i}}^{\mathrm{d}}(\mathrm{t})$$

where Ebest is the best position of the previous generation and #iteration represents the number of implementation stages in the current generation. Max_iteration approximates a maximum number of stages in each generation. α is a numerical education coefficient which ranges between 0 and 1. As it can be observed, in the initial iterations of each generation, the effect of the experiences of the previous generation is stronger than personal experiences. In the proceeding, the effect of personal experiences is gradually increased. The implementation procedure of DPSD algorithm is shown in Figure 1.

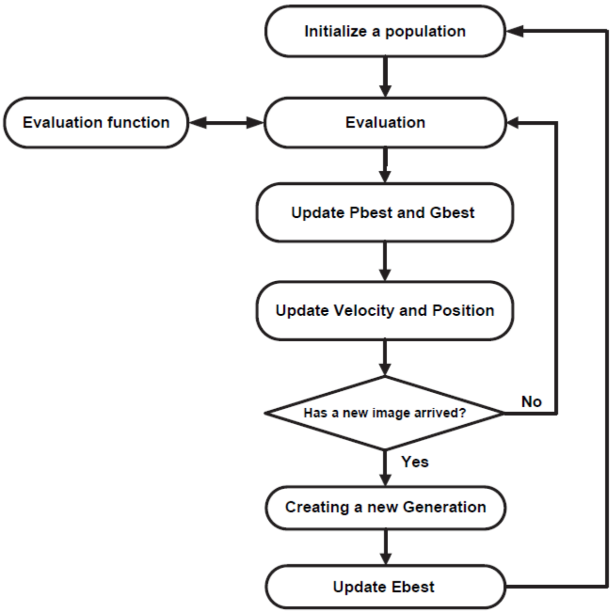


Figure 1: Implementation of the PSO algorithm.

2.2. Dynamic Particle Swarm Optimization

In this section, a new method is proposed for detecting small targets in infrared images based on a particle swarm optimization algorithm. In this problem, an image sequence of specific time span enters the algorithm, and the algorithm should detect the existing targets in each time span in the current image. One way to solve this problem is that when each image arrives, the optimization algorithm starts to process it and detect the targets before the next image. The main challenge of this method is the limited time of implementing the optimization algorithm, which can reduce performance. Therefore, the parameters within the proposed algorithm should be specified so that the best response is obtained in the shortest time. Moreover, one of the existing conditions in real-world infrared scenarios is that the successive images resemble so much that two successive images can be taken almost as one where the targets are slightly shifted. The proposed algorithm uses this observation to improve its performance. So, the targets obtained from each frame are used as potential targets in the next frame. This not only increases performance but also reduces search time. According to the aforementioned facts, the structure of PSO was changed in a way to be capable of detecting small targets in infrared images within limited time spans. In DPSD, the generation concept was created. Thus, the proposed algorithm includes generations, each with several iterations. In detecting targets in infrared images, when a new image enters, a new generation is defined which ends upon the arrival of the next image. Finally, the results of one generation are transferred to the next one. Thus, in modelling the movement of particles, in the proposed algorithm, besides the two dimensions of social interactions and personal experiences, the experiences of the previous generation are included too. This idea can be formulated with the following formulations.

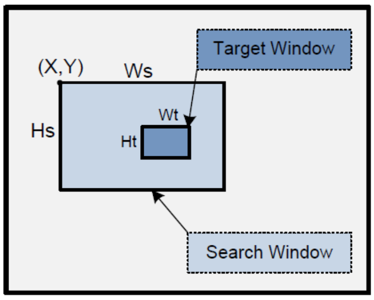
$$\mathrm{v}_i^d(t+1) = W \times \mathrm{v}_i^d(t) + \mathrm{rand} \times \alpha \times c_1 \times ({p_{best_i}}^d - \mathrm{x}_i^d(t)) + \mathrm{rand} \times (1-\alpha) \times c_1 \times ({E_{best}}^d - \mathrm{x}_i^d(t)) + \mathrm{rand} \times c_2 \times ({G_{best}}^d - \mathrm{x}_i^d(t))$$

$$\alpha = \begin{cases} \dfrac{\#Iteration}{Max\_Iteration} \, if \#Iteration < Max\_Iteration \\ 1 \, if \#Iteration > Max\_Iteration \end{cases}$$

$$\mathrm{x}_i^d(t+1) = \mathrm{v}_i^d(t+1) + \mathrm{x}_i^d(t)$$

2.2.1. Definition of Particles

As it can be observed from Figure 2, each particle is represented by 6 numbers, the first two of which show the position of the search window. The third and fourth numbers point to the dimensions of the search window and the fifth and sixth numbers indicate the dimensions of the target. It is trivial that any particle comprises 3 parameters: position of search area, dimensions of search area, and dimensions of target area. Moreover, the position of target area is not specified in particles. Considering the features of targets in infrared images, in the target area, the maximum illumination is that of the target. The proposed algorithm has used this fact in determining the position of target window in the search window. In this algorithm, the central point of the window is equal to the pixel position of maximum illumination in the search window.



X	Y	Ws	Hs	Wt	Ht

Figure 2: The particles for the given problem.

2.2.2. Evaluation Functions

Evaluation function or fitness function is a mathematical function whose input is one point (or one response) within the search space and whose output is a numerical value that indicates the fitness of that point as an optimal or target point. In DPSD algorithm, the input of the evaluation function is an area as the target window. The output of the evaluation function is a numerical value that shows the fitness of this area as the target. Indeed, the success of the optimization algorithm in detecting targets is directly dependent on the evaluation function. If there is a lack of proper evaluation of different points, target detection will deem impossible.

In DPSD algorithm, the evaluation function should determine the fitness of an area utilizing the illumination of the target window. Thus, to define an appropriate evaluation function, the feature of targets in infrared images needs to be considered. Overall, the following features can be attributed to small targets in infrared images:

–The intensity of illumination of targets is more than their surrounding points.

–The dimensions of targets vary depending on the distance from the camera.

–Considering the heat fields existing in atmosphere, the edges of target fade away and are not easily detectable.

Accordingly, the conditions required for an evaluation function are described as below:

$$F(T) = \left| \frac{1}{\sum_{(s,t)\in\Theta} \mathrm{T}(s,t)} \sum_{(s,t)\in\Theta} \mathrm{T}(s,t)\mathrm{I}(s,t) - \frac{1}{\sum_{(s,t)\in\Theta} \mathrm{N}(s,t)} \sum_{(s,t)\in\Theta} \mathrm{N}(s,t)\mathrm{I}(s,t) \right|^2$$

In this equation, I(x,y) represents the illumination of pixel (x, y); the Θ collection represents the existing pixels in target window; T(x,y) stands for the target illumination coefficient in pixel (x,y) and N(x,y) implies the background illumination coefficient in pixel (x,y). The relationship between T(x,y) and N(x,y) is defined below.

$$T(x,y) = e^{-\left(\frac{(x-x_c)^2}{2\sigma_x} + \frac{(y-y_c)^2}{2\sigma_y}\right)}$$

$$N(x,y) = 1 - T(x,y)$$

where x_c and y_c show the position of the central point within the target window. Moreover, σ_x and σ_y are set according to the dimensions of target window. These values are selected in a way that the illumination coefficients in the boundaries of the window are below 0.1.

3. Experimental Results

The dataset consists of 10 infrared images and 10 infrared image sequences including 990 images in total. These images include various false response sources such as the complex cloudy background, sea-sky background, high intensity edges, and a target close to high-intensity background clutter.

Although there were some missing parts in the algorithm, my implementation of the paper was working successfully. Some visual results are given in Figure 3, Figure 4 and Figure 5.

Figure 3: An example output of my implementation in which the target drone is clearly visible.

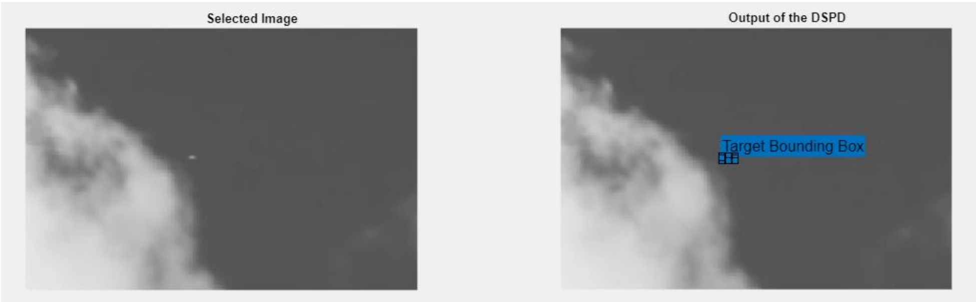


Figure 4: An example output of my implementation in which the target drone is small.

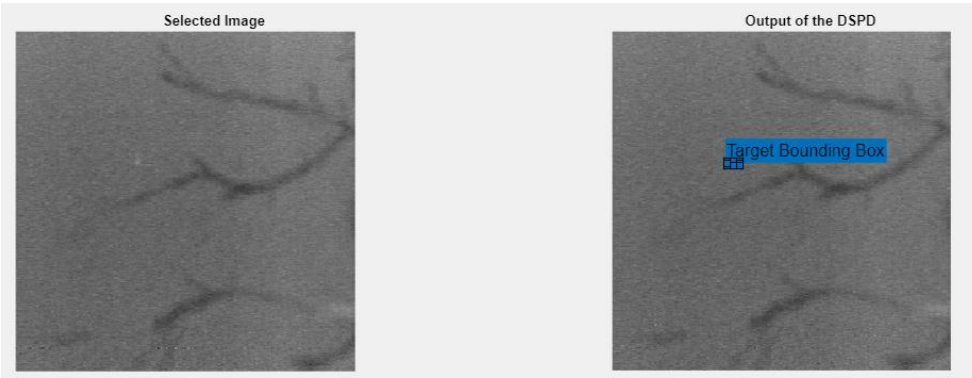


Figure 5: An example output of my implementation in which the target drone is small and blurry.

Considering the speed of my implementation with the one represented in the original paper, I can say that my implementation is also working in the same speed when the number of particles and number of iterations are similar.

4. Conclusions

I have implemented the DSPM algorithm to detect drones in infrared images in my term project. Considering the performance of my algorithm, it can be fairly said that it has good target detection performance. The results also showed that the speed of my algorithm is pretty good, even with the missing details of the original paper.