

# Evolution-Based Vision Algorithm with Fuzzy Fitness Function for Obstacle Detection

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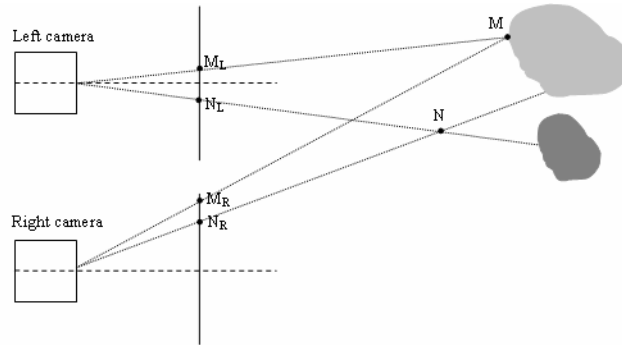
**Keywords:** Parisian evolutionary approach, fuzzy correlation, obstacle detection, vision.

## 1 Introduction

The proposed algorithm is a fast evolution-based vision technique for real-time obstacle detection [1]. Based on the Parisian approach [2] [3], our algorithm evolves a population of 3D particles which constitutes a three-dimensional representation of the scene. Evolution is controlled by a fuzzy fitness function able to deal with uncertain camera measurements, and uses classical evolutionary operators. The result of the algorithm is a set of 3D particles gathered on the surfaces of obstacles.

## 2 Fuzzy correlation

Assuming that the images have been rectified to have disparities only along the Y-coordinate axis, a particle is defined as a 3D point  $(x, y, z)$  that projects to the pixel  $(x_p, y_p)$  in the reference image and the pixel  $(x_p, y_p+d)$  in the right image. If the particle is within an opaque object of the environment, then corresponding pixels in the two images will have similar contrasts and similar neighbouring as shown in Figure 1. Conversely, if the particle is within a heterogeneous surface, similarity between corresponding pixels neighbouring will be low.



**Figure 1.** Pixels  $M_L$  and  $M_R$  are projections of particle  $M$ , are strongly correlated, pixels  $N_L$  and  $N_R$  receive light reflections from two objects with different contrasts.

We propose to calculate a fuzzy correlation cost to express the similarity between two corresponding pixels. We have defined three grey classes which are Black class, Average Class, and White class. Each one of the defined classes has its membership function. Let  $\mu_{black}(m)$ ,  $\mu_{average}(m)$  and  $\mu_{white}(m)$  be the degrees of membership of the pixel  $m$  respectively to the black class, the average class and the white class. We have used Gaussian membership functions centred in 0, 255 and 127.5. Two pixels  $m_1$  and  $m_2$  are strongly correlated if they belong to the same class. This

proposition can be expressed using fuzzy logic as follow: 
$$FC(m_1, m_2) = \max \left( \begin{array}{l} \min [\mu_{black}(m_1), \mu_{black}(m_2)], \\ \min [\mu_{average}(m_1), \mu_{average}(m_2)], \\ \min [\mu_{white}(m_1), \mu_{white}(m_2)] \end{array} \right).$$

Thereafter, we will use the notation:  $FC(x, y, z) = FC(m_1, m_2)$  with  $m_1 = (x_p, y_p)$  and  $m_2 = (x_p, y_p + d)$  projection of the 3D point  $(x, y, z)$ .  $FC(x, y, z)$  is the fuzzy correlation cost of the projections of the particle  $(x, y, z)$  into the reference and the right images.

### 3 Genetic conception of the algorithm

We have used a fuzzy fitness function that tolerates uncertainty of measurements. To favour evolution of particles towards obstacle surfaces, we propose the fitness function:  $Fitness(x, y, z) = \left| \nabla(x_p, y_p) \right| \times \left| \nabla(x_p, y_p + d) \right| \sum_{(i,j) \in N} FC(x_p + i, y_p + d + j)$  that characterizes similarity between support areas of the particle projections to the left and right images.  $N$  is a neighbouring introduced to have a discriminating comparison between the projections.  $\left| \nabla(x_p, y_p) \right| \times \left| \nabla(x_p, y_p + d) \right|$  are Sobel gradient norms on left and right projections of the particle [4]. Individual chromosomes are 3D particle coordinates  $(x, y, z)$ . Population is randomly initialized within the field of view of the reference camera from a distance  $d_{min}$  to the camera. Depths are allocated uniformly by distributing the inverse of  $z$  between zero and  $1/d_{min}$ . *Selection* is elitist and deterministic. Bidimensional *sharing* penalize particles that project into overcrowd area of the image by reducing their fitness functions by  $K \times N$ ;  $K$  is the sharing coefficient and  $N$  is the number of particles that projects in a sharing radius  $R$  around the current particle. *Mutation* operator that allow extensive exploration of search space uses an approximation of a Gaussian noise that will be added to  $(x, y, z)$  parameters. *Z* mutation is to add Gaussian noise to the inverse of  $z$  so that the variance of  $z$  mutation will be coherent with the density of particles that decreases with distance:  $z_{new} = \frac{z \times d_{min}}{d_{min} + z \times noise}$ .

Thereby, we have used mutations variances  $\sigma_x$ ,  $\sigma_y$ , and  $\sigma_z$  equal to  $R$  to be in the same order as the mean distance between two neighbouring particles. Mutation of  $x$  and  $y$  is calculated in a way to have independence between variance of the displacement of the image of the particle and its depth:  $x_{new} = x + (z_{old} \times noise) \times (d_{focal})^{-1}$ . The noise chosen for  $x$  and  $y$  is Gaussian and its variance is in the same order as the projection of the distance of a particle to its nearest neighbour  $\sigma_x = \sigma_y = \sqrt{N_{pixels} / N_{pop}}$ . We have defined a *barycentric crossover*. Given two parents  $M$  and  $N$ , the algorithm gives their offspring  $F$  as:  $\overline{OF} = \lambda \overline{ON} + (1 - \lambda) \overline{OM}$  ( $\lambda$  is randomly chosen in  $[0, 1]$ ). An example of execution in a robot environment scene is illustrated in Figure 2.

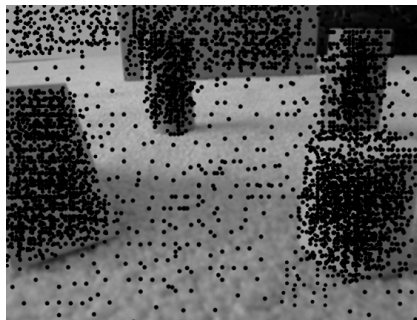


Figure 2. Convergence of our algorithm after 100 generations.

### References

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