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Optimal Detection of Oil Contamination at Sea by the FPSO Algorithm

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Abstract

Leakage of oil from pipelines and oil tankers into seas and oceans is ecologically important and can have significant social and economic impacts on the environment. An early detection of deliberate or accidental oil spills can reduce serious hazards that may threaten coastal residents and help identify pollutants. Iran has been surrounded by seas from the north and the south and they provide us with valuable natural resources, in general, and oil reserves in particular. Besides, the seas are where oil is mined and oil tankers pass. Therefore, protecting the seas against oil contamination is essential. Due to the vastness of seas and the need for early detection of contamination source, modern methods must be employed to prevent excessive environmental damage. Unfortunately, a few studies have been conducted on it to date. In the present study, a number of robots controlled by the Fuzzy Particle Swarm Optimization (FPSO) algorithm were used to discover the source of contamination. In this paper a z coefficient was added to FPSO algorithm derived from fuzzy logic and contamination condition. This z coefficient informed the velocity of particles in a PSO model. We showed that using a fuzzy logic can improve the treatment of standard PSO algorithm in detecting oil contamination.

Keywords: Oil Contamination, Fuzzy Particle Swarm Optimization, Robot.

1. Introduction

Factors such as extensive use of offshore wells, marine oil transportation, oil tanker accidents, oil discharges from ships, and damage to oil facilities by hostile countries make oil contamination an issue of great consideration. Oil contamination has long-term and short-term effects. Short-term effects are assigned into two categories. Included in the first category are the decrease of light penetration, reduction of dissolved oxygen, and damage to aquatic ecosystems. These are due to the formation of an oil coverage on the surface of seawater and its resultant oxygen deficiency and suffocation. The second category results in oil poisoning. However, in most cases it is the seabed ecosystem which is seriously affected by oil contaminations in that a layer of oil deposits at seabed.

According to the report published by the American Academy of Science (2002), annually, 3.1 million liters of oil spill into seas and oceans. In 1980, 3.2 million liters of oil leaked into oceans half of which was leakages from damaged and rotten oil pipes [1]. A lot of research has been conducted on different types of robots with electric sensors to detect contaminants in hazardous environments. Robots must find the suspected source of emissions and then, clean the contaminated area [2, 3, 4, 5, and 6]. In [7], the concentration of gradients is used to estimate the distance of contamination from the source. In some studies only a single robot has been employed to discover the source of contamination [3 and 8]. But, there is a tendency to use multi-robot systems [9, 10, and 11]. In [12 and13], satellite images were utilized to compare different methods such as SAR, MISR, ALSO and MODIS. These methods use image processing techniques to identify a given contaminated area.

The following part of the present study addresses several methods available to clean up oil contamination. The third part deals with PSO algorithm and its problems. Subsequent to that comes a summary of fuzzy systems. Then, the simulation of detection by FPSO and PSO methods is discussed, and after that, the results of the simulation phase are expounded.

2. Oil Contamination Cleaning Methods

The cost of contamination clearing depends on several factors such as the type of oil hydrocarbons, amount and intensity of contamination, geographic coordinates, economic status and the biological properties of the incident location, weather and sea conditions, the time of incident, the clearing method used, and its efficiency. Although preventing contamination to spread has been always the best solution, fast and appropriate response to such disasters requires having sufficient knowledge of different contamination collecting methods. When the sea is calm, oil spills can be collected by making some kinds of barriers. Three types of these barriers are floating, pneumatic, and chemical. Floating barriers are usually used in anchorages and oil transferring areas. Pneumatic barriers work by releasing compressed air into perforated pipes. In the chemical barriers, some special chemicals are added that make oil gelatinous or even solid. On the other hand, if the sea is stormy, the afore-mentioned methods are not applicable. In such cases, oil absorbent materials such as straw can be used to clean the coast. Another proposed method is to burn oil and plod it under coast sand. In this method, microscopic organisms decay the buried oil. This kind of bio remediation is one of the main methods of cleaning up the environment in that living organisms, especially bacteria, fungi and plants dissect environmental contaminants into nontoxic compounds [1, 14, 15, 16, and 17].

3. Particle Swarm Optimization (PSO)

PSO is an optimization technique based on population. The method was put forward by Kennedy and Eberhart (1995) [18]. The main idea of PSO has been inspired by collective behaviour of fish or birds in their searching for food. Suppose that there is only a single piece of food in a specific area and a group of birds are looking for it. One of the best strategies is to follow the bird that has the least distance to the food. This strategy is the basis of PSO algorithm. In PSO algorithm, each solution, which is called a particle, is equivalent to a bird in a bird collective motion pattern. Each particle has a suitability value that is calculated by a suitability function. In the bird motion model, the closer a particle is to a given target (i.e. food), the more suitable it is. Furthermore, each particle has a velocity that determines the direction of its motion. By following the surrounding optimum particles, each particle continues its motion in a given space. In this algorithm, each of the collection members tries to adjust its direction by the best personal and group experiences to find out the final solution. If the solution is a local optimum, then, particles move sequentially toward it as the best solution. However, the standard algorithm of PSO does not present any strategy to exit this local optimum. This is the biggest disadvantage of standard PSO causing it to fail to solve multi-peak problems especially in large search area. One of the solutions to deal with the problem local optimum in PSO is to use mutation [19, 20, and 21]. In [19, 20], Gaussian mutation and its modified versions are used in standard PSO. This method has been tested in two-dimensional functions and the test results showed that this type of solution provides better answers in comparison with those provided by standard PSO. In [21], Cauchy's distribution has been employed for mutation. Based on the method, every particle can mutate by a certain probability that is shown by P_{mutate}. When a particle is selected for mutation, it is possible that each vector component of the particle mutates by 1/d probability with the d standing for the dimension of the problem. For random mutating of every component of a particle, Cauchy's distribution is selected and added to the related component of particle's vector. This method is useful for problems with huge search areas.

In standard particle swarm motion algorithm, the total velocity of a particle is used to calculate the particle's velocity in the next iteration. In every iteration, a particle's velocity is composed of two parts. The first part is the current particle's velocity, and the second one, is related to the best personal and group experience. Without the first part, an algorithm changes to a local search near the best particle and without the second one, it seems that an algorithm goes through an overall blind search. Particle swarm motion algorithm combines the both parts and tries to make a balance between overall and local search. In [20], a new parameter called inertia weight is introduced. The inertia weight is a coefficient that defines the particle's current velocity and is used to calculate the velocity of a particle in the next iteration.

There are other solutions for the problem of local optimums problems coming from combining other algorithms such as genetic algorithm, hill climber's method, annealing algorithm, and fuzzy logic with PSO algorithm [22, 23, and 24].

In some PSO versions, a particle selects some parts of swarm as topological neighbours. In such cases, the particle only deals with these selected parts and the best local solution (lbest) is used instead of g best.

$$V_i\ (t+1) = w * V_i\ (t)\ +\ c_1 * rand *$$
$$(P_i\ (t) - X_i\ (t))\ + c_2 * rand *$$
$$(P_g\ (t) - X_i\ (t))$$
$$X_i\ (t+1) = X_i\ (t) + V_i\ (t+1) \tag{1}$$

The right side of Eq.1 consists of three parts: the first is the current velocity of a particle. The second and third parts show the change in a particle's velocity and its turning to the best personal and group experience. Figure.1 shows these parts.

If we do not consider the first part of Eq.1, then, the velocity of a particle is only determined by the current velocity of the particle and its best experience of the particle and collection.

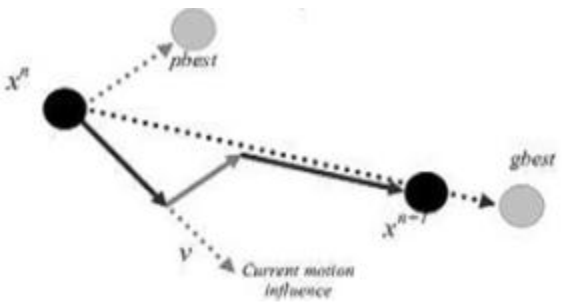

Fig.1 . Current velocity of particle

In this way, the best particle of the collection remains fixed in its place, and the other ones move towards it. Without the first part of the Eq.1, the search space of the group motion of particles becomes smaller and smaller gradually. In cases like this, the local search only happens around the best particle. However, by only considering the first part of Eq.1, particles move through their ordinary way until they meet a restrictive wall. This means that they have a kind of overall search [21].

4. Fuzzy Systems

Fuzzy logic was proposed for the first time by the Iranian scientist Lotfi A. Zadeh in 1960. His classic work published in 1965 was the beginning of a new direction in science in general, and system and computer engineering in particular.

Fuzzy logic is a rather new technology that can be applied to simulate the systems with complicated mathematics and probabilities. To make the process of system designing simpler, more accurate, and more efficient, use is made rules based on linguistic variables and the knowledge of an expert. Control systems based on fuzzy logic have high explicitness for decision-making and more understandable results. Fuzzy logic is a generalization of the Boolean's logic. Since in classic logic everything is described by binaries (0 or 1, white or black, yes or no), fuzzy logic shows Boolean's true propositions by an accurate degree. The membership function of a fuzzy set is similar to classic functions. In a special state, it is a curve that indicates the mathematical mapping of each the point of a space onto the degree of membership. This degree of membership is either one or zero. The most common shape of membership functions is triangular.

The processing step called inference engine works based on a set of IF-THEN fuzzy rules. Each fuzzy system has some rules that are saved in its dataset. For example, if we receive a good service, then, usually we tip. In this statement "service" and "tip" are linguistic variables and "good" and "usually" are linguistic phrases.

There are two major procedures to reach a fuzzy inference. The first model is Mamdani's fuzzy inference introduced in 1975. The second one presented in 1985 is Takagi Sugeno inference method. These methods are similar in input fuzzification and fuzzy operands. However, the outputs of Sugeno method are linear or constant functions and Mamdani's are fuzzy membership functions. In this paper, we applied Mamdani's method.

The last step in a fuzzy method is defuzzification. There are several methods for defuzzification such as highest membership, centre of gravity, Weighted Average Defuzzification Technique, and mean of maximum. In the present study, we use centre of gravity method for defuzzification [26, 27].

5. Simulation Results

To conduct the study, 15 robots were theoretically used, as shown in Figure.2, Figure.3, Fig.4, Fig.5 and Fig.6. These robots were transferred

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to the intended location in the sea and after the search time, they could find the main source of contamination and all the robots could get to it. These robots were equipped with “865 NDIR” sensor for analysing the concentration of oil in seawater [28]. This sensor measures the amount of carbon in the solution and then, indicates the oil concentration in water and its range between 0 to 100 ppm.

The robots were interconnected via a wireless network. The objective function is:

$$\boldsymbol{C} = \boldsymbol{K} * \sum_{i=1}^{m} \left(\frac{\mathrm{p_i}}{\mathrm{r_i^2}}\right) \tag{2}$$

Where C is the amount of concentration, P is the distribution rate of source, r is the distance to source, K is a constant coefficient, and m is the number of sources. In the equation, concentration has a reverse relation with distance. It means there is a low oil concentration if we are far from the contamination source.

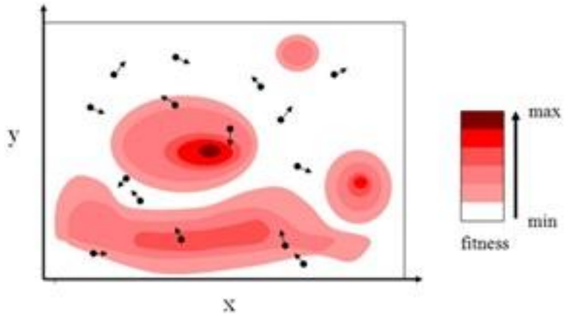

Fig.2. The location of robots in seawater for the first time

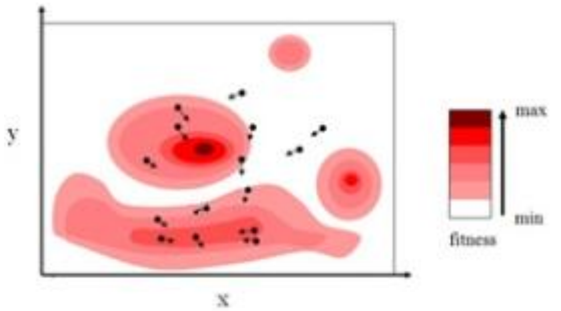

Fig.3. The search results for second time

Inputs to fuzzy systems for each robot are C in the three following cases {L (Low), M (Medium), H (High)} and change in concentration (delta C) in the seven cases, namely{NH (Negative High) , NM (Negative Medium) , NL (Negative Low) , Z(Zero), PL (Positive Low), PM (Positive Medium), PH (Positive High)}. The output is Z in the three cases {L, M, H} that influences robots’ speed as shown in Eq.3. In Eq.3 we take c1=c2=2.

$$V_i\ (t+1) = Z * [w * V_i\ (t)\ +\ c_1 * rand * (P_i\ (t) - X_i\ (t))\ + c_2 * rand * (P_g\ (t) - X_i\ (t))] \tag{3}$$

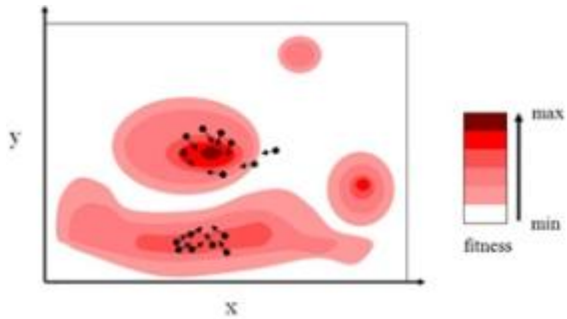

Fig.4. The search results for third time

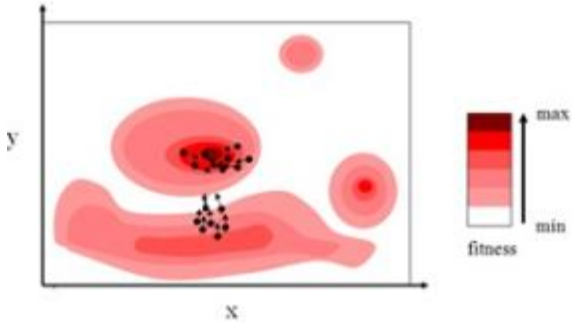

Fig.5. The search results for fourth time

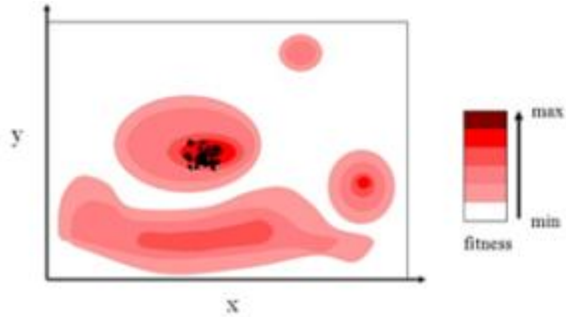

Fig.6. Detection the source of oil spill

Inputs and outputs are fuzzified as Figure.7 to Figure.10. Here, we used Mamdani’s inference engine and max-min method. Considered rules are listed below:

1. If (C (concentration) is L) and (deltac is Z) then (z is H)
2. If (C (concentration) is M) and (deltac is Z) then (z is M)
3. If (C (concentration) is M) and (deltac is pM) then (z is L)
4. If (C (concentration) is H) and (deltac is pL) then (z is L)

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As mentioned before, the centre of gravity method was used for defuzzification.

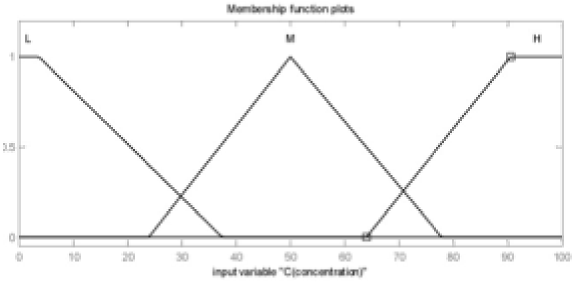

Fig.7. Fuzzification of concentration

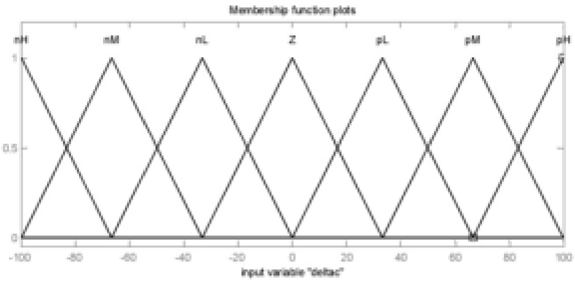

Fig.8. Fuzzification of concentration variations

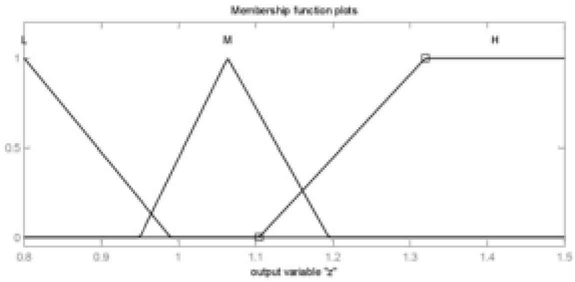

Fig.9. Fuzzification of output (Z)

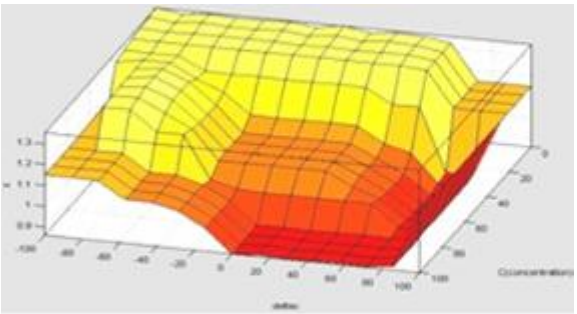
Fig.10. Surface plot of output and input sets

The results of simulations are shown in Figure.11. This Figure indicates that PSO algorithm in combination with fuzzy logic (FPSO) provides us with better results than PSO algorithm in different aspects.

6. Conclusion

Damage to pipelines and oil tankers cause oil to leakage into oceans and seas. This contamination has social, ecological, and economic effects on the given surrounding environment. Quick detection of a contamination and its removing can reduce the hazardous influences on coastal residents. In this paper, we used FPSO and PSO methods to detect the source of oil spills. The PSO algorithm proved useful for discovering the source of contamination. Owing to the importance of time factor in finding the source of oil spills, using fuzzy logic promoted the behaviour of standard PSO algorithm. It was also found that FPSO was quicker than standard PSO in detecting the source of contamination. In the present study, an attempt was made to focus on the automatic methods of oil leakages and to find ways to detect the source of contaminations quicker and safer.

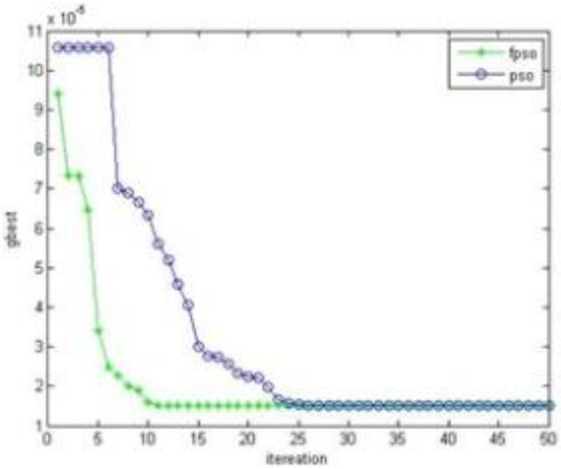

Fig.11. Diagram of the PSO and FPSO convergence

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