Hybridization of Moth Flame Optimization and Gravitational Search Algorithm and its application on detection of Food Quality

Design Oriented Project Report

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by

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1 Abstract

Gravitational Search Algorithm is an optimization algorithm inspired by the Newton law of Gravitation and the Newton's laws of motion. Moth Flame Optimization is another optimization algorithm, motivated by the locomotion of moths around a light source. Both these algorithms, have tried to model the search agents, and altered its properties like mass, Gravitational constant, fitness, location etc. in order to find the most optimal value. The optimization algorithms usually solve only a class of problems, and therefore the search for a faster, and more comprehensive algorithm is always on. By combining the Moth Flame Optimization and Gravitational Search Algorithm, the performance is expected to improve across various measures.

Project Food Sense aims to use this improvement in order to find the degree of rottenness of various food items. This will help decrease the losses in food storage, and early detection of spoilage of food, in order to minimize monetary losses due to food and storage. This hybrid method is used in improving the results of segmentation. We have successfully implemented it over K-means and Multi-level thresholding.

On application of our optimization algorithm to K-means clustering, we aim to reduce the mean squared error from each data point to the centroid of the cluster. Since the initialization of the cluster centers is random in the original algorithm, the mean squared error varies with each application, even on the same dataset. Through the application of optimization algorithm, we aim to bring down the mean squared error and bring uniformity to the application of K-Means clustering.

For Multi-Level Thresholding, the brute force approach to finding the thresholds is a very expensive process. Finding the threshold, for multiple clusters, where each threshold could be a value anywhere between 0 and 255, the task becomes very expensive. Also, this is mostly a manual process. However, the optimization algorithm aims to bring down this complexity by using multiple search agents, each trying to find the most optimal threshold value, while communicating to each other the most optimal value. This reduces the algorithm complexity, and

in turn automates the whole process of finding the right values. This has multiple applications as the problem complexity increases as the dimensions or color space changes. However, this method can be extended to multiple color spaces, finding the best threshold values for each color space parallelly.

In addition to the vision data, odor sensors also find their place in the midst. Intuitively, the food items are checked for quality by looking and smelling them, when done manually. Our aim to automate the process of detecting deterioration is therefore supported by the use of QCM gas sensors.

2 Literature Review

2.1.1 Image processing Techniques:

Artificial Neural Networks: Inspired from the biological neural system, this machine learning technique tries to simulate the human intelligence. Here, the physical properties extracted from the images can act as quality factors. It results in near human level performance in areas of color, content, shape, and texture inspection. This has been applied in many food categories like fishery, fruits, vegetables, grain and meat and has resulted in accuracy of detection nearly 90%.

Optimization Techniques: Classification can also be done using optimization techniques. Appropriate fitness function needs to be chosen and optimized accordingly. Rule sets can be generated in order to do classification of test data.

Color Space:

Color spaces are representations of different colors using different models. There are wide variety of color spaces to choose from each having its own benefits.

RGB: Widely used color space, since it works in a way similar to human vision. Views each color as a mixture of red, green and blue in different proportions.

1. HSV: Unlike RGB it separates luma (illumination information) from chroma (color information). Mainly used when dealing with variable illumination. HSV images can be easily segmented.

2. LAB: The components of this color space are Luminance, a and b(color opponent dimensions). This color space is efficient in digital image manipulations i.e. handles shadows, noise etc well.

3.1.2 Nature Inspired Algorithms

There has been research going on in this area for a long time now and there have been several algorithms that are inspired from nature like the human mind, ants, bees, Geo sciences etc. A subset of nature inspired techniques in Swarm Intelligence. Swarm Intelligence refers to the collective behaviour of several individual agents communicating with each other. It is a totally decentralized mechanism. Agents share knowledge among themselves by communicating. This is one of the most used techniques for optimization. There are algorithms like Ant Colony Optimization, Swarm Particle Optimization, Bee Clustering Algorithm, Gravitational Search and Moth Flame Optimization each algorithm mimicking the swarm behaviour found in nature.

2.1.3 Previous Research in Food Safety

Shape, size, and position can be consistently and rapidly measured using computer vision. With the recent developments of algorithms and the improvement of computer hardware, the sensitivity and ranges have been widened for samples of larger size and more complex shapes. Therefore, computer vision has been extensively applied for food-quality assessment.

Mechanisms for food safety already exist in almost all countries but most of them involve manual inspections which in turn take time and resources. Below are examples of food products that have been studied extensively.

Apples: Quality of bicoloured foods has been evaluated extensively. Multispectral imaging has been employed to evaluate the quality of bicoloured apples (Unay et al., 2011). Geometrical and textural properties are invaluable in identifying defects in food. Kang and Sabarez have also worked on a new segmentation algorithm to analyze dried apple slices. There has also been research to predict the color changing process of a freshly cut apple.

Oranges: Skin defects especially help in identifying defects in oranges. Multivariate image analysis approach has been combined with computer vision to detect skin defects in oranges. Blasco et al, 2009 identified 11 types of defects in five spectral areas.

Bananas: During ripening process bananas exhibit a gradual transformation in colour and texture. At a rapid speed, banana peel degrade form greenish-yellow to dark spotting. (Quevedo et al, 2008) showed that fractal texture analysis based on spectral Fourier analysis was a potential and promising method for evaluating spots in banana peels.

There has been research going with respect to various other food products such as Potatoes, Meat, Berries, Dates Mangoes, Pears etc.

Recently nature inspired algorithms which comprise of algorithms modelling the human mind, artificial immune system, swarm intelligence and geo science based computing have emerged as efficient techniques to handle a diverse set of problems. Fuzzy Set Theory, Genetic Algorithms, Swarm Intelligence based Algorithms, etc are examples of Nature Inspired Techniques. Nature Inspired Algorithms have been applied to a wide variety of fields ranging from Computer Vision, Clustering, Learning, General Optimization Problems to name a few.

Nature Inspired Metaheuristic Algorithms have been used extensively for Partitional Clustering. Genetic Algorithms and Swarm Intelligence based algorithms have been proven to give good results in partitional clustering. An in depth survey of nature inspired metaheuristic algorithms used for partitional clustering can be found[1].

There have also been approaches like [2] where the Gravitational Search Algorithm has been used for for data clustering. In this algorithm, some candidate solutions for clustering problem are created randomly and then interact with one another via Newton's gravity law to search the problem space. The performance of the presented algorithm is compared with three other well-known clustering algorithms, including k-means, genetic algorithm (GA), and particle swarm optimization algorithm (PSO) on four real and standard datasets. Experimental results confirm that the GSA is a robust and viable method for data clustering.

There have also been hybrid approaches combining nature inspired algorithms with the classical algorithms like in [3] where a combined hybrid approach of the famous K-means algorithm along with Gravitational Search Algorithm is presented. The quality of the clusters and convergence speed of the GSA has been enhanced by incorporating a k-means algorithm in generating the initial population for GSA. It is important to create a good initial population because the performance of GSA and most of the population-based algorithms are affected by the quality of the initial population. In the proposed algorithm, we try to incorporate the advantage of the k-means algorithm into GSA. K-means is a simple and fast algorithm that is able to find a near optimal solution in a reasonable amount of time. The generated solution by k-means later will be used by GSA as one of the candidate solutions.

Nature Inspired algorithms also have found applications in computer vision and related areas, Multi Threshold Segmentation for example. There have been approaches where segmentation process is considered as an optimization problem[4] approximating the 1-D histogram of a given image by means of a Gaussian mixture model whose parameters are calculated through the DE, the PSO and the ABC algorithm. The statistical analysis of the results showed a superior performance of DE not only in minimizing the Hellinger distance between the original and the candidate histogram but also performing such a minimization in less evaluations of the mentioned cost function based on distance.

2.1.4 Previous Research in Food Safety using Nature Inspired Algorithms

With consumer concerns increasing over food quality and safety, the food industry has begun to pay much more attention to the development of rapid and reliable food quality estimation systems. Computer Vision, being a non intrusive, non destructive approach has the potential to estimate the characteristics of food products with advantages like speed, ease of use and minimal sample preparation. Specifically with Computer vision systems are capable of classifying foods into different grades, detecting defects and estimate properties like color, shape, texture and surface defects etc.

2.1.5 Computer Vision

This paper talks about a variety of sensors such as hyperspectral and multispectral imaging, vibrational spectroscopy, as well as biomimetic receptors[9]. Data is acquired by any or a mixture of the above methods. The resulting data acquired from the above-mentioned sensors require the application of various case-specific data analysis methods for the purpose of simple understanding and visualization of the acquired high-dimensional dataset, but also for classification and prediction purposes.

Vibrational Spectroscopy, Hyperspectral Imaging and Multispectral Imaging , Biomimetic Sensors are nature inspired array of sensors designed to mimic the olfactory and gustatory systems of humans called E-nose and E-tongue respectively. Acquiring data from one or more of the previously introduced sensors results in multivariate datasets, i.e. a large number of variables (x-data) connected to an observed value or category (y-data).

Chemometrics, Machine Learning and Evolutionary Computing methods are used to extract information from the data extracted. Supervised as well as Unsupervised learning is applied to generate models which are then validated later on. The paper then goes on to talk about the sensor quality, external features, bruise detection and other quality parameters.

The journal talks about the kind of hardware used for a standard computer vision setup and goes on to talk about the computer vision techniques used for food safety of Bakery products, Vegetables, Fruit, Grain, Prepared Consumer foods[10].

2.1.6 Meat and Fish

Visual inspection is used extensively for the quality assessment of meat products applied to processes from the initial grading through to consumer purchases. McDonald and Chen (1990) investigated the possibility of using image-based beef grading in some of the earliest studies in this area. They discriminated between fat and lean in longissimus dorsi muscle based on reflectance characteristics, however poor results were reported. Greater accuracy was found in a study by Gerrard et al. (1996) where R2 (correlation coefficient) values of 0.86 and 0.84 for predicted lean colour and marbling were recorded, respectively, for 60 steaks using image analysis. Li et al. (1997) measured image texture as a means of predicting beef tenderness.

Colour, marbling and textural features were extracted from beef images and analysed using statistical regression and neural networks.

2.1.7 Fruit

Computer vision has been used for such tasks as shape classification, defect detection, quality grading and variety classification. Defect segmentation on Golden Delicious apples was performed by CMV (Leemans et al., 1998). A colour model developed was used as a standard for comparison with sample images. The transform converts a spherical object image to a planar object image allowing fast feature extraction, giving the system an inspection capacity of 3000 apples/min from the three cameras, each covering 24 apples in the field of view.

2.1.8 Vegetables

The necessity to be responsive to market needs places a greater emphasis on quality assessment resulting in the greater need for improved and more accurate grading and sorting practices. Computer vision has shown to be a viable means of meeting these increased requirements for the vegetable industry. Shape, size, colour, blemishes and diseases are important aspects which need to be considered when grading and inspecting potatoes. Machine vision systems have been developed for grading potatoes using a HSI (hue, saturation, and intensity) colour system. The system was able to differentiate between good and greened potatoes with an accuracy of 90% by representing features with hue histograms and applying multivariate discriminant techniques. Computer vision has also been applied for the automated inspection and grading of mushrooms. The features considered were colour, shape, stem cut and cap veil opening.

Similarly a paper presents a review of various computer vision approaches applied for food safety of meat, fish, vegetables, fruits etc[13].
This paper especially talks about the kind of learning techniques applied in food safety algorithms. They range from Artificial Neural Networks used for classification of cereal grains, fruits especially apples and fish and meat and vegetables, Segmentation is discussed as a preprocessing step where in ANN is applied on the segmented image. Statistical Learning, Decision Trees and their applications to various food products has been discussed[14].

3 Optimization Algorithms

Optimization problems refer to the process of finding the best possible solution for a given problem. This can be finding the minimum value, if the problem is a minimization problem, or the maximum value if the problem is a maximization problem.

A proposed heuristic to curb the problem of local minimum is to use swarm intelligence, where the search agents are spread across the domain, and they communicate some information in each iteration, in order to reach the global minimum. Such algorithms are usually divided into 2 phases:

Exploratory phase

The first phase of the multi-agent search, where the search agents are spread across the solution domain. This is often done randomly, in order to increase the chances of search agents being spread across the whole domain, ensuring better chances of avoiding the local minima.

Exploit phase

This is the later phase of the swarm based optimization algorithm. This happens after some iterations of the exploratory phase, when the search agents have certain amount of information about the fitness of the other agents.

There is no clear distinction between the two phases, and may overlap. Additionally, there is no heuristic to mark the transition between the two, and is dependent on the algorithm to switch form the exploratory phase to the exploitation phase. If the algorithm takes more time to explore, the chances of returning some local minima reduces. However, it may lead more time, i.e. number of iterations, to converge to the optimal value. It is therefore a trade-off between the accuracy of the result and the time taken to reach an optimal value.

3.1 Moth Flame Optimization

Moth Flame Optimization (MFO)[16] is a nature inspired algorithm which is motivated by the navigation of moths in night. Moths use the moon as reference to travel through the night. This mechanism of navigation is called as Transvers Orientation. In this method, the moths move at a fixed angle with respect to the moon. Since the moon is at a very large distance, the motion is effectively linear.

However, in an experiment, it was observed that in presence of a light source extremely close to the moth, leads to the moth confusing the light source with the moon, and navigates similarly with respect to the light source, as it does with respect to the moon. However, since the light source is too close, the moth falls into a deadly spiral, converging into the flame.

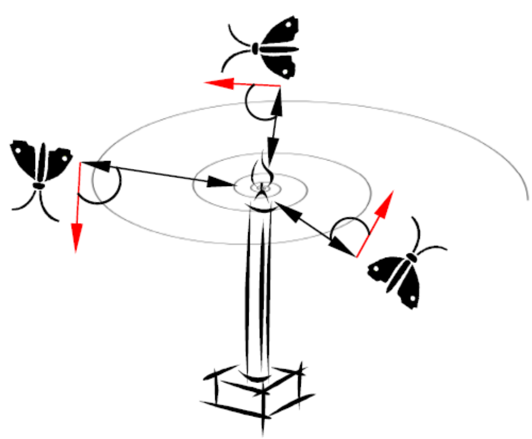
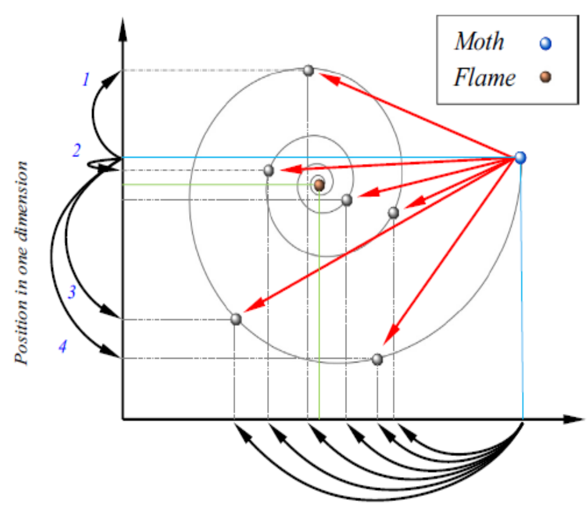


Fig. 2. Spiral flying path around close light sources.



In this algorithm the candidate solutions (search agents) are the moths. The problem's variables are the positions of the moths in the hyperspace.

3.2 Gravitational Search Algorithm

Gravitational Search Algorithm (GSA)[17] is another nature inspired algorithm which is motivated by the Newton's law of Gravitation, and the laws of motion. It is based on the concept that two masses in space attract each other with a force.

$$F_{ij} = G\frac{M_{aj} \times M_{pi}}{R^2},$$
$$a_i = \frac{F_{ij}}{M_{ii}},$$

In this algorithm, the candidate solutions are the masses, spread across the hyperspace and each has an associated mass, which dictates the motion of all the search agents, which eventually converge to the most optimal value.

3.3 Hybrid Algorithm

The algorithms are themselves very powerful. By using multiple search agents, and adding some degree of randomness in the locomotion, avoid local minima to a large extent. However, the hybrid algorithm seeks for faster convergence, while maintaining the exploration of both the algorithms. This is expected to be achieved through the combined locomotion in every iteration.

MFO, due to its spiral locomotion avoids the local minima, as the agents are not directly attracted towards the optimal flame in a linear trajectory. On the other hand, the locomotion is in a logarithmic spiral, which lets other moths explore the domain, for better optimal value.

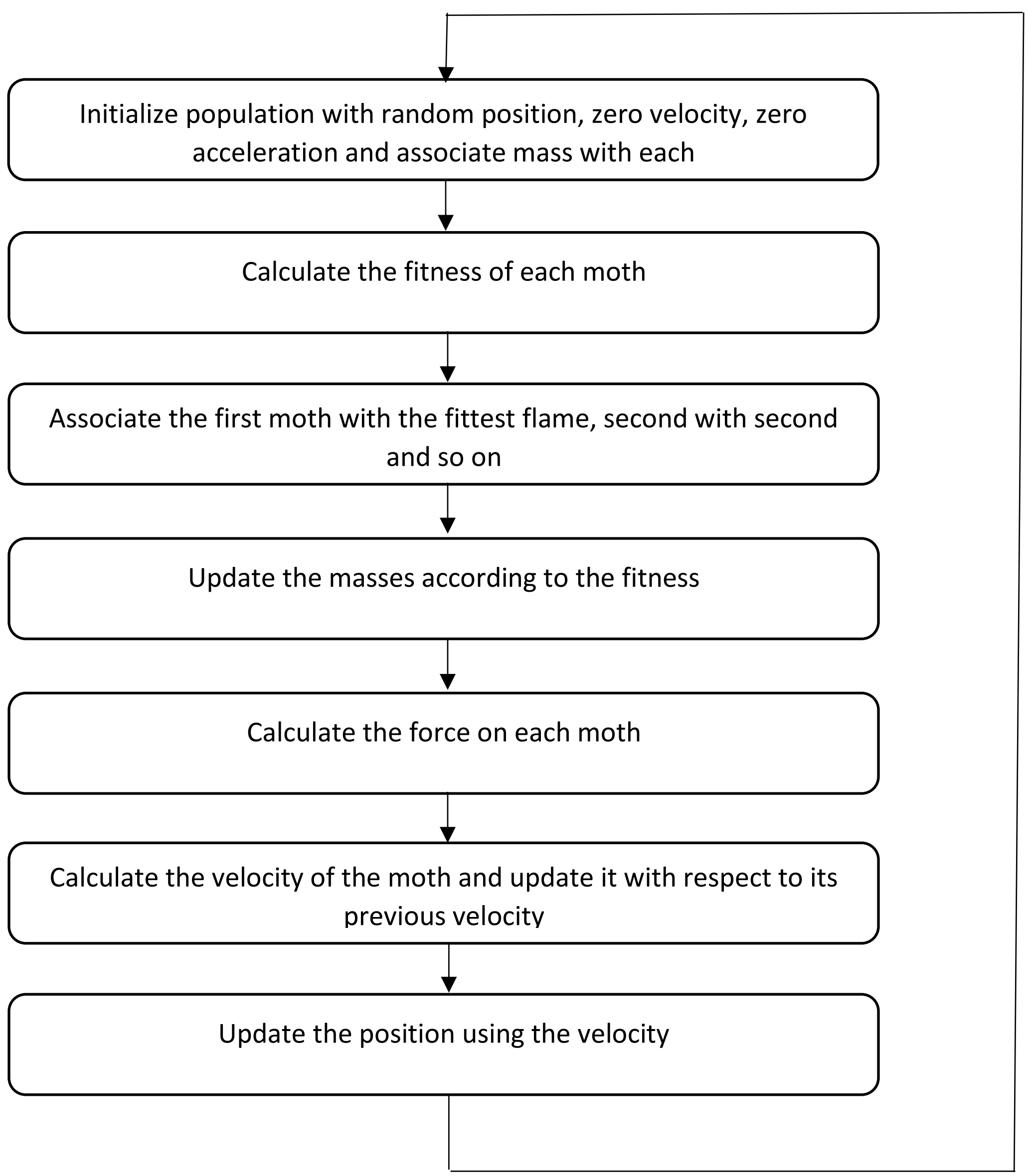
GSA, on the other hand, uses a linear force on the search agents while it seeks to converge to the most optimal value. This typically introduces a dominance of the exploitation over exploration.

Thus, in the hybrid algorithm, the exploration of MFO and the exploitation of GSA is exploited, in order to achieve better results, while maintaining the integrity of the optimization algorithms individually, and evading the convergence to any local minima.

3.3.1 Justification for hybridization

The algorithm exploits the nature of the moth flame optimization, by using its exploratory in nature, and utilizes the exploitation of the gravitational search algorithm. The intuition behind this approach to hybridize these two algorithms is that the MFO utilizes the logarithmic spiral for exploration, while the GSA uses the linear motion for locomotion. This enables the hybrid algorithm to exploit both the properties of the individual algorithm and therefore fit together, covering what the other fails to cover.

The fitness measure is mass for GSA while the fitness measure for MFO is distance to the fittest flame. This adds the variability to exploit both the behavior in a single algorithm, thus rendering the hybrid as a better fit. MFO makes the search agent go around the fittest flame, while GSA ensures faster convergence by bringing all the search agents closer to the fittest search agent. Thus, these algorithms are compatible, and produce the desired effect.

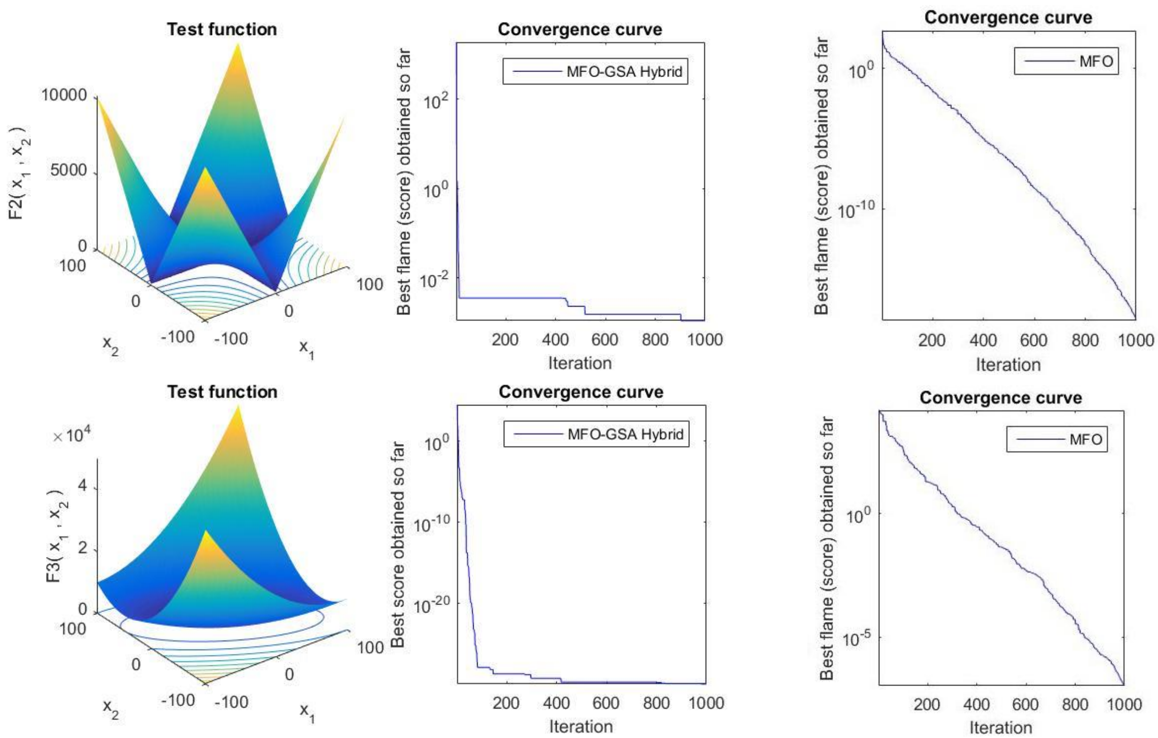


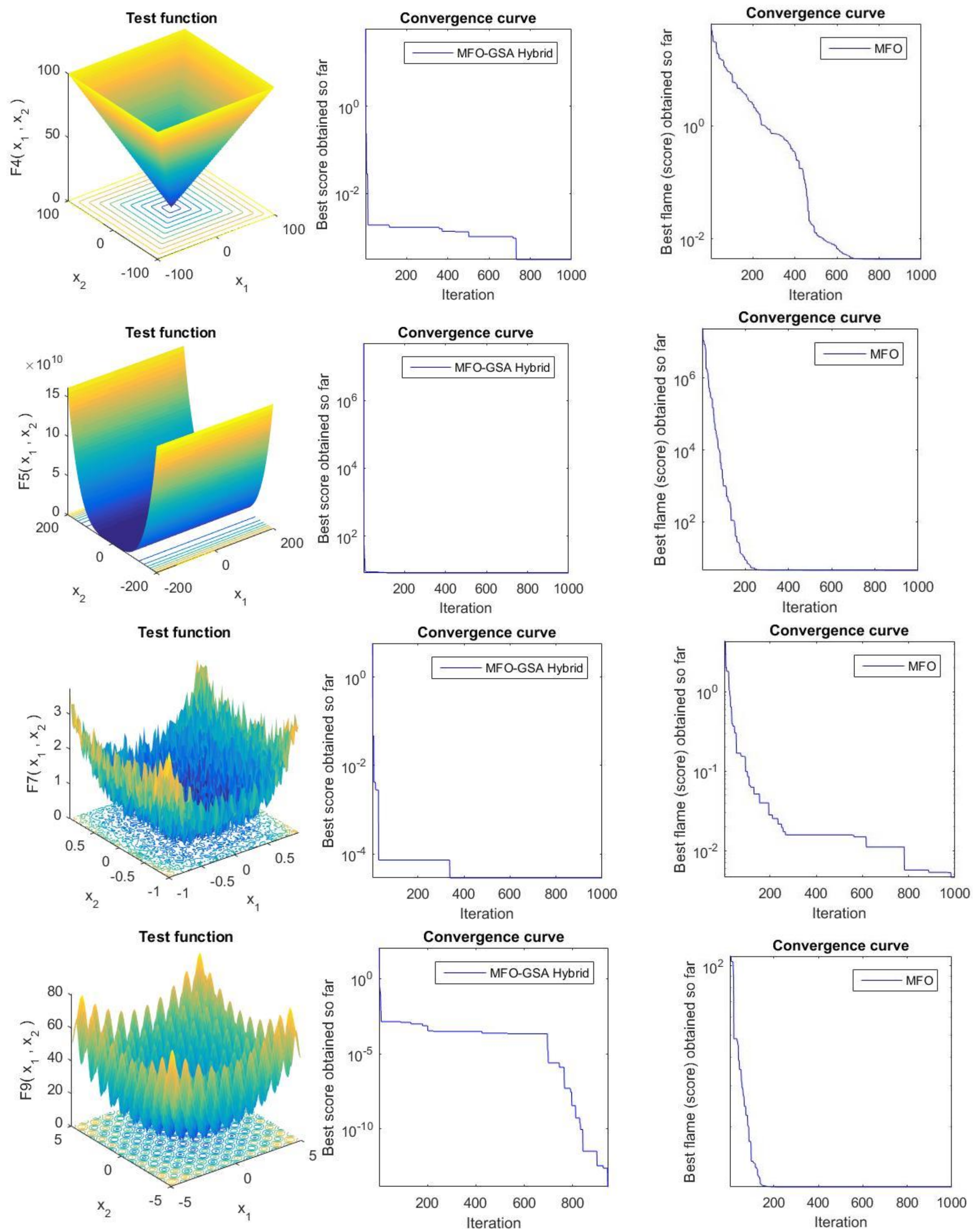
3.3.2 Pseudo Code

```
initialize moth_position, moth_velocity, moth_acceleration
calculate initial fitness for each moth
while(iteration < max_iteration)
        update flame_number
        if (iteration == 1)
                F = sort(M)
                OF = sort(OM)
        else
                F = sort(Mt-1, Mt)
                OF=sort(Mt−1, Mt);
        end
        for i=1: n
                for j=1: d
                        Update r and t
                        D(i) = |F(i) – M(i)|
                        M(i) = D(i) . e^bt . cos(2∏t) + F(j)
                end
        end
        G = G0(1/iteration)^b
        for i=1:n
                mass(i) = 1/fitness(i)
                for j=1:n
                        r = moth_position(i) – moth_position(j)
                        F = G*mass(j)/r
                End
                Moth_velocity(i) = moth_velocity(i)*rand(0,1) + F
                Moth_position(i) = moth_position(i)*rand(0,1) + moth_velocity(i)
        end
end
```

4 Testing Hybrid Optimization on Benchmarks and Results

FUNCTION	MFO	HYBRID	GSA	GA
F1	6.6092e-21	5.9991e-17	1.321152	21886.03
F2	2.6592e-15	0.0010437	7.715564	56.51757
F3	7.2411e-09	2.2439e-17	736.5616	37010.29
F4	0.0043443	0.00031035	12.97988	59.14331
F5	15.7733	8.0849	77360.4184	313.21418
F6	0.12108	0.32572	2.86418	52.64496
F7	0.0046347	2.8854e-05	1.03951	20964.83
F8	-2879.4219	-2471.4722	-102.5649	-13.37504
F9	10.9445	0	25.46556	2.14891
F10	4.4409e-15	0.00011668	5.32221e-10	5.4981e-5
F11	0.22639	2.9199e-14	6.1948e-5	7.4198
F12	8.4387e-32	0.024027	1.28685e-25	0.02959
F13	1.992	2.9821	12.4944	4.5195





Test function
F4(x1 , x2)
x2
x1
Convergence curve
MFO-GSA Hybrid
Best score obtained so far
Iteration
Convergence curve
MFO
Best flame (score) obtained so far
Iteration
Test function
F5(x1 , x2)
x2
x1
Convergence curve
MFO-GSA Hybrid
Best score obtained so far
Iteration
Convergence curve
MFO
Best flame (score) obtained so far
Iteration
Test function
F7(x1 , x2)
x2
x1
Convergence curve
MFO-GSA Hybrid
Best score obtained so far
Iteration
Convergence curve
MFO
Best flame (score) obtained so far
Iteration
Test function
F9(x1 , x2)
x2
x1
Convergence curve
MFO-GSA Hybrid
Best score obtained so far
Iteration
Convergence curve
MFO
Best flame (score) obtained so far
Iteration

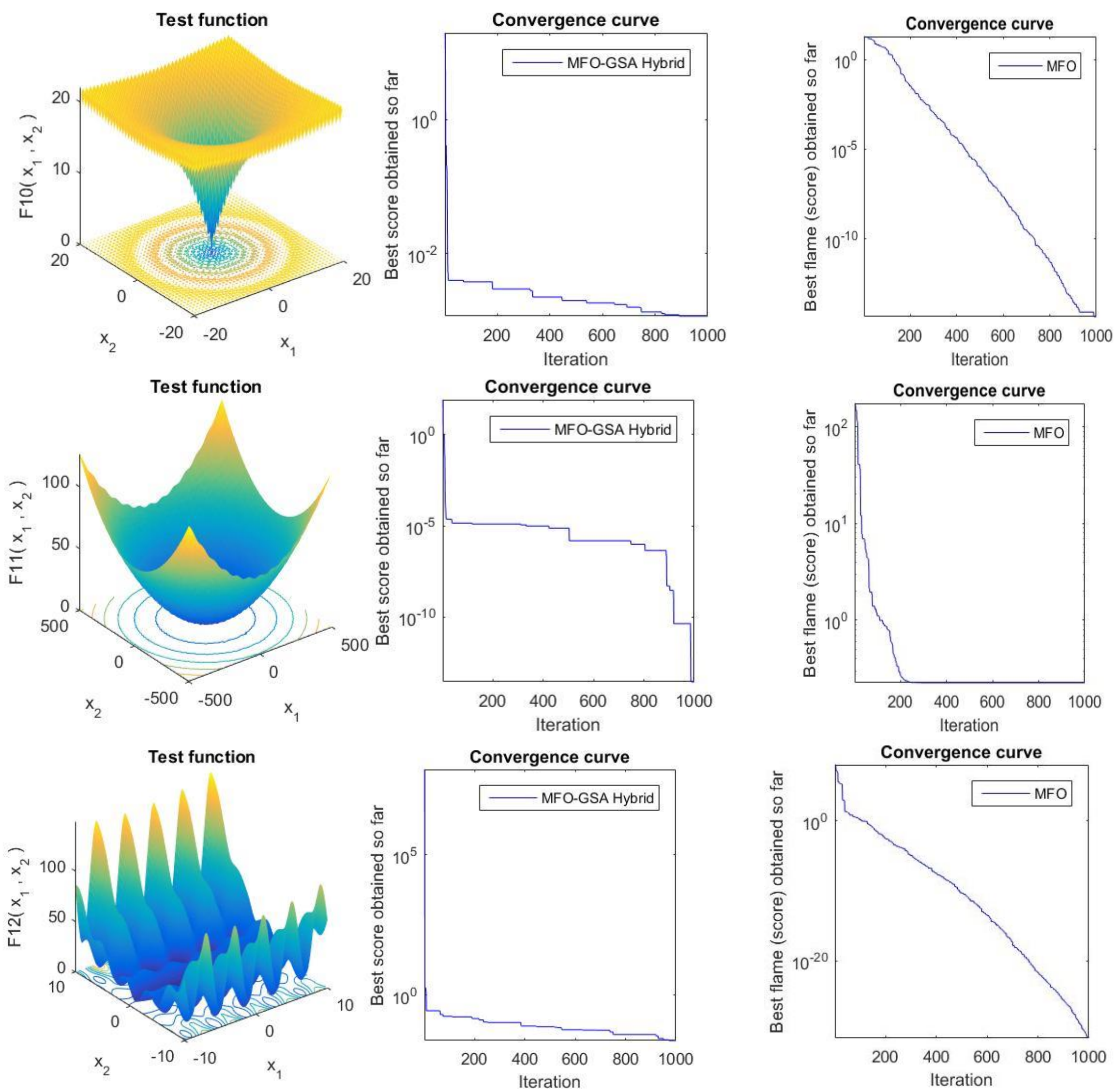


Figure: Comparison between Hybrid and MFO

5 Image Segmentation – Computer Vision

5.1 Image Segmentation using K-means clustering algorithm:

K-means Clustering: This algorithm requires as an input parameter, the number of clusters that are finally needed. The number is represented by K; hence the name K-means. From the set of data points, K random points are initialized as cluster centers and points are assigned to the cluster centers using the minimum distance criterion. The goal is to make sure that points in the same cluster are as similar as possible and points in one cluster are as different as possible from the points in other clusters. The similarity function can be chosen to be anything, in the spatial data case it is Euclidean / Murkowski distance. If documents are being clustered, the document matrix can be used. For images, the pixel values, intensity values, color values, hue values etc. can be used to define similarity

1. Parameter initialization: The initial K-mean points are initialized randomly from the set of pixels provided. The value of each pixel in each dimension is chosen randomly from the set of existing points, for this reason the initial K – mean points may not represent actual points in the image. But their components would be definitely being available in the image.

2. Hard Assignment of Pixel to Clusters: Given that each of the K clusters has a mean point Muk[equation], every point in the set of data points is assigned to the cluster to which it is most similar. Similarity is calculated based on Euclidean distance between pixels. After this, every point is assigned to exactly one cluster Ck.

3. Parameter Re computation: The new means of the clusters are computed based on the points assigned to the cluster in the first iteration.

Steps 2 and 3 are repeated till convergence, which typically means that no pixel shifts from one cluster to another between iterations.

The K-means segmentation technique was applied on the apple dataset. The images below show the results for various types of diseased apples.

BLOTCH

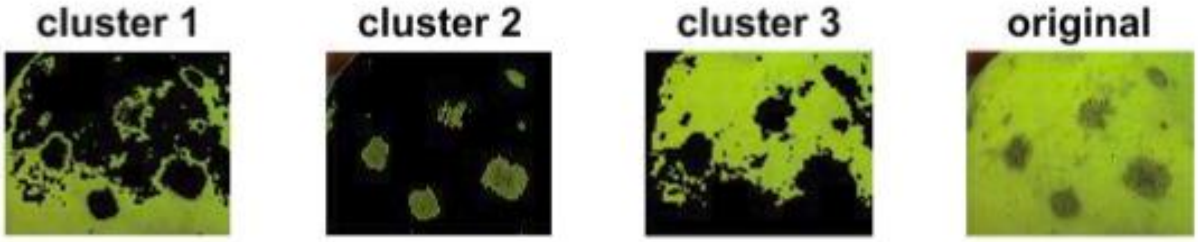


Fig. Cluster output for apple blotch

ROT

Fig. Cluster output for apple rot

SCAB

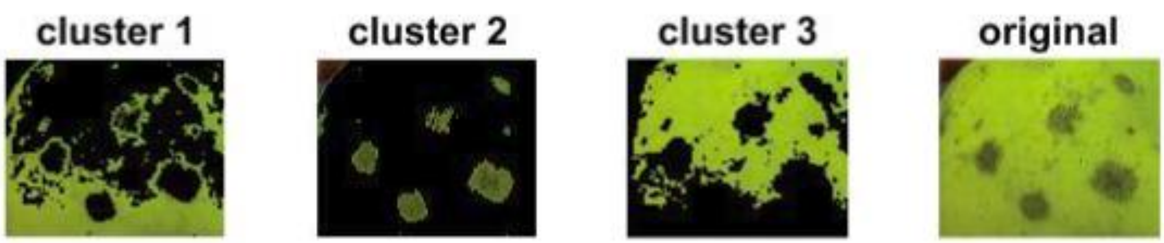


Fig. Cluster output for apple scab

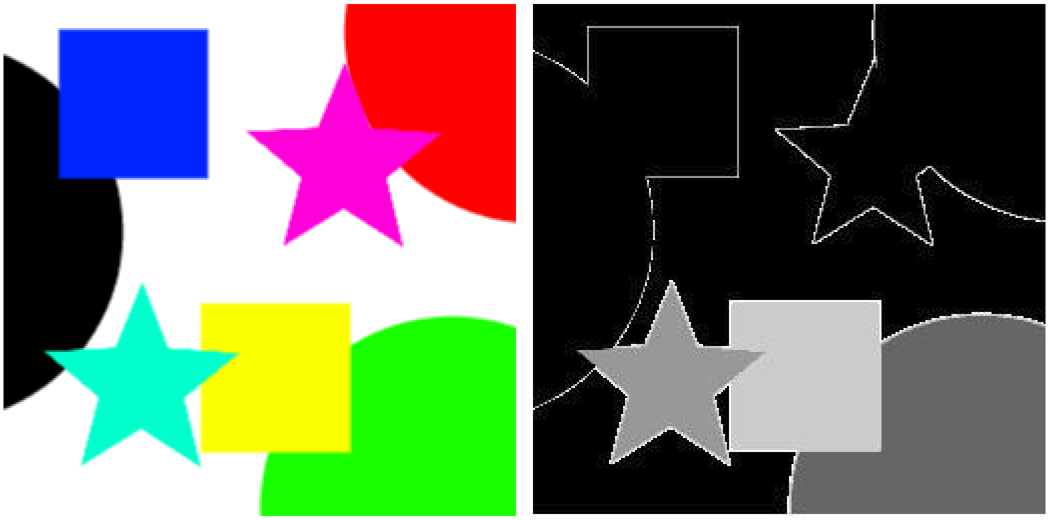


Fig: Segmentation results for standard color image

Fig: Segmentation results for rot

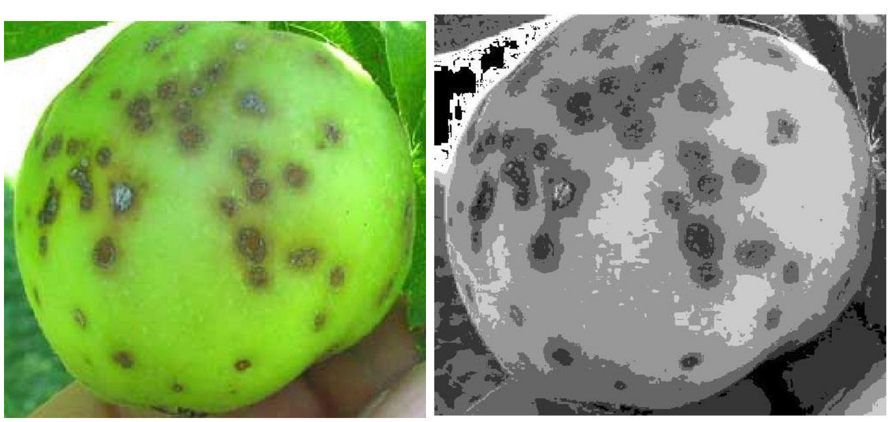


Fig: Segmentation results for scab

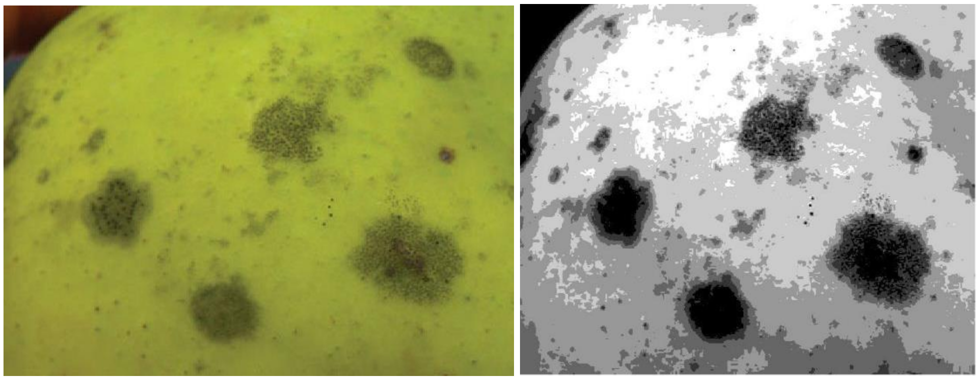


Fig: Segmentation results for blotch

6 Feature Generation:

Features generated would then be used for classification. The following are the features I have tried.

6.1 Local Binary Patterns:

Local Binary Pattern is a texture analysis technique. It runs on the basic concept of assigning binary values to each pixel. These values are generated through analysis of its neighbors. It is computationally inexpensive and yet effective that it finds its application in multiple computer vision problems like facial recognition. It is a robust algorithm for it works even in different illuminations and environments.

6.2 Grey Level Co Occurrence Matrix:

The grey level co-occurrence matrix is a distribution matrix which represents the co-occurring values in the vicinity. It signifies the relationship of a sub-image of a fixed size to its surroundings. It calculates the frequency of a pixel value occurring in its vicinity either horizontally or vertically or diagonally.

7 Conclusion

As evident from the results, the hybrid optimization algorithm performs better in F3, F4, F5, F7, F8, F9 and F11 by reaching a more optimal value. However, the values are comparable in other functions except F1, F2 and F12. However, as seen in the graphs, the convergence is much faster in those cases, where the values are comparable. Therefore, our algorithm shows considerable improvement over MFO alone.

The newly proposed segmentation algorithms, optimized K-means and multi level thresholding using the developed hybrid algorithm has performs well. The segmentation techniques are not problem specific, and can find its application in any field of computer vision. The optimization algorithm improves upon the results of the segmentation for K-Means, and automates the threshold selection in Multi-Level Thresholding.

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