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Evaluation of the Accuracy of Genetic Algorithms in Orientation Estimation of Objects in Industrial Environment

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***Abstract*—**The world of machine vision and robotic vision revolve around a wide array of techniques and methodologies built around image processing. While conceiving and developing any such technique, due importance is accorded to the nature of the problem to be addressed and the ultimate purpose to be realized. For instance, realizing object recognition in an image environment having multiple objects, realizing object detection and recognition in an image environment characterized by occlusion and clutter and many other unique scenarios like these. For realizing object detection, localization eventually leading to object recognition in environments characterized by multiple objects and occlusion and the environments having objects undergoing different rotations in an image plane; a proper estimate of object orientation is central to an appropriate pose estimation of object which in turn plays a vital role in accurate recognition of the object. For realizing object recognition in such unique scenarios, orientation and pose estimation will go hand in hand. In the present study, an attempt is made to accurately estimate the orientation of a single industrial object in an image using genetic algorithm (GA), a nature inspired evolutionary technique for optimization and thus facilitates in evaluating the potential and accuracy of the GA when used as a standalone GA in providing a correct orientation estimate. The analysis of the results presents the GA as a reliable, potent and efficient tool for suitably estimating the orientation of the single object in the image.

***Keywords*—** Object detection; object orientation; robotic vision; image segmentation; image thresholding; genetic algorithm; selection; mutation.

I. Introduction

Object detection and recognition are indispensable and integral to the domains of machine vision and robotic vision systems [1]. The functional quality of robotic vision systems employed in both industrial robots for industrial automation and service robots for household applications is greatly influenced not only by the hardware involved but also by the choice of the software designed and deeply embedded in such systems to drive them for the purpose of realizing object detection and recognition [1], [2]. These impart the desired capability to the robotic vision systems for facilitating inspection, localization, registration, and manipulation of the objects for automation in different industries and extending the desired services in household applications. Object detection and recognition in the real environment has always presented formidable challenges to the engineering and scientific community since it first appeared on the horizon of the machine vision research [3]. Recognizing and detecting the objects of a particular class such as a human face, a car, a bird, an animal etc. in the static images make it even more challenging [4]. Notwithstanding the various complexities and diverse challenges associated with the domain of machine vision, the research in this domain has grown rapidly beyond these complexities especially in the last two decades since it has been both intensively and extensively researched across the scientific and engineering fraternities [5]. Object detection and recognition constitute an indispensable component of modern day intelligent systems which have shaped and cut across a broad spectrum of disciplines in contemporary human life such as security, health, defence, surveillance, medical diagnostics etc. where the issue of object detection and recognition need to be handled quickly and accurately. The research on object detection and recognition algorithms has spearheaded significant advancements in factory and office automation, assembly line industrial inspection systems as well as chip defect identification systems [6]. It has also resulted in appreciable and tangible progress in medical imaging, space exploration and biometrics. Different researchers over the years have approached the problem of object recognition and localization by developing methodologies based upon different techniques which are defined by the nature of the problem to be addressed. It can be easily observed that object detection and recognition are significantly influenced by the confounding parameters of pose, orientation, scale of object and environment parameters such as intensity, illumination [5]. The parameters of pose and orientation are observed to acquire more prominence when object detection and recognition are to be realized in environments which are characterized by occlusions, multiple objects in images, cluttering, overlapped objects in images and where the objects of a specific category undergo different orientations in the image plane [7-10]. It is also observed that the orientation parameter is given more attention than position and scale parameters when developing techniques centered around the

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accurate pose estimate of the object to realize object recognition in such scenarios because even a small difference in orientation parameter can induce a significant change in the appearance and shape of the target object for the machine and robotic vision systems to recognize them appropriately and this can lead to unpredictable and undesired results [11], [8].

In this research paper, we present our work which is centered around the implementation of the GA in a standalone mode and which is upgraded from its original design used earlier in the detection of industrial objects in our previously presented work [12] to measure accurately the orientation of the objects which in the present study are the tools of everyday use in industrial work environment such as a screw driver, a plier, adjustable spanner etc. This work is undertaken not as a comparative study but as an experimental endeavour to evaluate the accuracy of the GA in estimating the orientation of the industrial objects when the GA is designed to work alone on its own, taking complete charge of the problem of estimating the orientation of the object and eventually leading to object detection utilising only its inherent evolutionary attributes such as initialization, reproduction, cross-over, mutation. In this way, this work implements the GA and explores its potential, when used in standalone mode, in accurately estimating the orientation of a single object in non-occluded and uncluttered static image environment.

The outline of rest of this paper is structured as follows. Section II highlights some of the relevant research contributions made in the field of object detection and recognition centered around the relevance of accurate orientation and pose estimation in diverse environments which inspired our research. Section III gives major insights into the relevant technical constituents which form the foundation of the presented work. Section IV gives an analysis of the proposed GA design with regard to its evolutionary attributes and highlights the flow chart of the proposed GA. Section V provides the outline of the salient steps in the sequence of flow of GA. Experimental results and performance evaluation are covered in Section VI. Conclusion and future scope are summarized in the last section i.e. Section VII.

II. Related Research and Contributions

Informative literature and work documentation are available in abundance on different techniques and methodologies adopted to realise object detection and localization in diversified contexts taking due cognizance of the relevant object attributes such as orientation, scale and position. Motivating works by different researchers also provide creative insights into the versatility of GAs when it comes to its implementations in variety of real world domains such as business, sciences, medical diagnostics etc. to extract reliable and optimal solutions in optimisation problems integral to such fields. Several such substantial works which contributed in motivating, guiding and charting the course of this work may be grouped into three distinct categories: orientation—a valued contributor in object recognition, image segmentation, and genetic algorithm.

A. Orientation—A Valued Contributor in Object Recognition

Scale invariant feature transform based method (SIFT) to successfully recognize the position and the orientation of the objects for an automated pick and place robotic system used in industrial and household applications was proposed by Patil and Chaudhari in their research paper [7]. They emphasized that recognizing the correct location and orientation of the given object are central to the ultimate purpose of a robust robotic vision system. In addition to reviewing different techniques and algos implemented by different researchers for the purpose of object detection and localization, the authors in their experimental results showed that SIFT outperforms the other methods based on other feature descriptors and emerges as the best method for object localization and recognition in pick and place robotic systems.

A simple object recognition method was presented using the singular value decomposition (SVD) of the object image matrix and a functional link neural network for a bin picking vision system to be employed in a bin picking robotic system. The problem of recognizing objects inside the bin is quite complex and challenging since the appearances and shapes of the objects undergo tremendous change owing to their varied degrees of orientation for the bin picking robots to recognize them easily. The authors Hema C.R. et al. [8] did not utilize the visual features of the pixels but used singular value (SV) features properties of the image matrix for its analysis and feature extraction. The properties of the SV features played an important role in the recognition of the objects with different orientations.

The authors U. Bagci et al. [11] in their research work presented a model based multi-object recognition method to assist in recognition of anatomical structures in medical image segmentation. They observed that the orientation parameter requires more attention as compared to the scale and the position parameter in estimating the accurate pose of the structure in the image as even a small difference in orientation can lead to an inappropriate recognition. The authors statistically analyzed and evaluated that the mean Herrmitian and Cholesky metrics provided more accurate orientation estimates than other Euclidean and non-Euclidean metrics.

A suite of algorithms was presented after implementation on an autonomous robot for the purpose of its navigation so as to determine the most optimal trajectory to reach its destination while moving through the obstacles on its course by C. Ilas et al. [9]. The authors implemented two algorithms for navigation. First one was for the accurate estimation of the object orientation based upon the canny edge detection and K-means clustering and the second one was for the determination of the collision free paths after comparing the distances between the obstacles on the path. The output of the first was used by the second algo and both could work on robots with medium computational resources.

M. Villamizar et al. [10] presented an approach for the robust detection of the specific classes of objects that might appear in the still images under different orientations. Instead of addressing the problem by using the traditional multiple classifiers specifically trained at different orientations leading

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to high computational costs in both training and test stages, the authors split the approach in the two stages, the object pose estimation and the orientation specific classification for efficient detection of objects in images. The classifiers in both the stages were based upon the boosted combination of random ferns evaluated densely over local histograms of oriented gradients (HOGs). The experimental results showed the method to be competitive with the state of the art methods with the benefit of being computationally more efficient.

B. Image Segmentation

Navneet kaur et al. presented a colour image segmentation algorithm based upon BFO technique [13]. The basic step in the proposed algorithm was the quantization of the colours in the image without degrading the quality of the colours. The proposed algorithm implemented region growing to obtain the segmentations in the image and these segmentations generated the objects of interest in the image.

In their research paper, the authors Amrinder Singh and Sonika Jindal argued that image segmentation affects the subsequent processes of image analysis such as object classification, scene interpretation [14]. Researchers are continuously trying to improve the quality of image segmentation by fusing BFO with GA and PSO. Their technique used the ANFIS edge detector for edge detection on digital images. It involved a system with the learning capability of neural network and the advantages of rule based fuzzy system.

The authors Manjusha Singh et al. in their research paper conveys that image segmentation occurs as the preprocessing step before image pattern recognition, image feature extraction and plays an important role in computer and machine vision especially in human tracking [15]. In their work, the authors have voted in favour of methods of image segmentation based upon the visual principle as these can be employed as hierarchical approaches that do not require any user input and are found to perform well especially for the image with single object in prominence.

Rajeshwar Dass et al. [16] in their research paper showed that the implementation of the image segmentation techniques can be usefully utilized in the navigation of the robots, filtering of the noisy images, medical applications like location of tumors, cancerous cells, computer-guided surgery, in locating objects in satellite images e.g. roads, rivers, forests etc. The authors have clearly deduced that despite several segmentation techniques available, there is not a single method which can be considered good and applied for different types of images equally well.. So there is a great need to develop a unified approach to image segmentation which can be applied to all types of images.

C. Genetic Algorithm

Bajpai and Kumar in their research paper conveyed that GA is quite reliable in generating optimal solutions to optimization problems in signal processing, robotic vision systems, medical imaging, object localization, stock market and variety of other fields [17]. They also argued that in order to make GAs more effective and efficient, they should be combined with other good optimization techniques such as BFO etc.

The authors Karkavitsas and Rangoussi in their research paper presented GA approach to the problem of object registration in the medical images of the blood cells [18]. Their work also highlighted underlying basic mechanisms of work in GA such as parent selection, reproduction etc. The work showed that the success and efficiency of the GA is critically dependant on the choice of the evaluation (fitness) function and an appropriate choice of the parameters.

P. Kanungo et al. [19], in their research paper proposed a GA based crowding algorithm to determine a suitable threshold value from the peaks and valleys of the histogram with bimodal features which can be used for the purpose of Image segmentation. They emphasized that gray-level thresholding is an important step in any image analysis application. This GA based approach worked well for images with bimodal features but did not perform well for images with trimodal features.

A method in which GA was used on Fourier descriptors which were used to represent the shape descriptive features of an object was presented by the authors Mahmood Ul Hassan et al. [20] in their research paper. The authors also compared the GA based method with the PSO technique in their experiments and observed that GA based technique outperformed the PSO, since the GAs work in the direction to maintain a population of potential solutions to a problem at any stage and not just one point solution as can be seen in techniques like PSO.

III. Technical Approach—Key Components

The major components which constitute the core of the proposed methodology for orientation estimation of objects in industrial environment are covered in this section. Although the proposed methodology is centered around the design of the GA but for its proper understanding, it can be conveniently partitioned into two key components, image thresholding, the Genetic Algorithm--an overview.

A. Image Thresholding

Proper segmentation of an image is the foundation of object detection and recognition in machine vision [21]. The purpose of image segmentation is to locate the edges or boundaries of object in the image which help in feature extraction and finally object detection and recognition. Edge detection is a very important step in image analysis and image segmentation. Object detection and recognition directly depends upon the quality of the edges detected. Image segmentation can be realized by adopting different techniques and approaches. The popular among these are histogram thresholding, edge based segmentation, region based segmentation which itself employs different techniques such as thresholding, splitting and merging, region growing [22].

Gray-level-thresholding is an important first step in any image analysis application whose purpose is to acquire a binary image of a gray scale image, i.e., the image which contains any two pixel values either 0 or 1. In gray-level-thresholding, a gray scale image is divided into distinct

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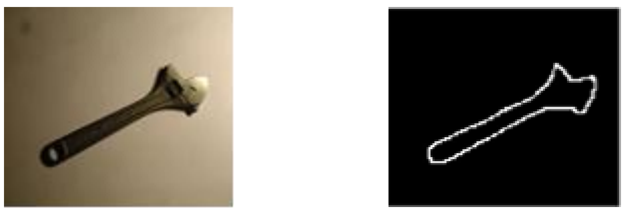
components like foreground objects, where pixel value is 1 and background objects, where the pixel value is 0 by partitioning the pixels in the gray scale image into foreground (object) and background classes based upon the relationship between the gray level value of a pixel and a significant gray level threshold parameter selected in that gray level image in a systematic way so as to separate the object from the background in the image [19].

In the proposed methodology, gray level thresholding has been incorporated into the GA design taking due cognizance of this fact that a RGB (True colour) image can actually be resolved into three distinct gray scale images where each of the three gray scale images correspond to the R-component (Red colour), G-component (Green colour) and B-component (Blue colour) image of the actual RGB image. The implementation of the gray level thresholding in the proposed GA results in the binary image of a RGB image shown in figure 1 with the boundaries or edges of the object in the RGB image properly detected and clearly shown outlined in white colour against a black background.



(a) (b)

Fig. 1. Preprocessing of the input RGB image. a) RGB image of an adjustable spanner, b) Preprocessed binary image with edges shown in white.

B. *The Genetic Algorithm—An Overview*

The GAs for the last 20 years have been extensively in use and gained much popularity in the domains of image processing, pattern recognition, machine vision and object detection. GA is a nature inspired search and optimization technique which derives it's functional character from the principles of natural selection and genetics [23]. Today the engineering and scientific community relies on this technique as a potent answer to wide array of real world optimization problems in fields like digital signal processing, robotic vision systems, medical imaging, object detection and recognition just to mention a few [17].

The use of GAs is highly recommended by the researchers in all such problems where an optimal solution is to be extracted from a potentially huge solution space. In such optimization problems, the GAs have been observed to outperform the other traditional optimization techniques such as calculus based optimization, hill climbing, feed forward ANNs (Artificial Neural Networks) [17], [23]. GAs also score over other nature inspired evolutionary techniques like simulated annealing, PSO etc. in the context that GAs always work in the direction of maintaining a population of potential solutions to a problem at any stage of their processing and not just one point solution as can be seen in techniques like PSO [20].

The GA is a search heuristic that generates a population of individuals (potential solutions) and allows them to evolve to a state of maximum fitness by following Darwinian rules of natural selection and evolution. Thus the GAs promote the survival of the fittest [23], [24] and this fittest corresponds to the optimal solution of the search and optimization problem.

Any simple GA incorporates the following five steps in its functioning which are derived from nature's principles of natural selection and genetics. It is incorporation of these principles in it's functioning that imparts GAs its quintessential genetic character. The five primary operations employed by GAs in their functioning are initialization, evaluation and selection, reproduction, cross-over and mutation.

IV. The Proposed GA Design Analysis

The GA which is implemented in the present work in order to evaluate the orientation of the object in industrial environment is actually an upgradation of its original design as implemented in our previously presented work [12] and incorporates the same inherent attributes which constitute the foundation of any simple, modified and hybrid GAs. This section presents an overview of the analysis of the GA designed and upgraded by us for the purpose of orientation estimation with regard to the essential genetic attributes of initialization, evaluation, selection, reproduction, cross-over and mutation.

A. *Initialization*

Initialization in GA refers to the randomly generated initial population of the individuals (potential solutions) in a search problem [17]. In GA parlance, each such individual is a chromosome which comprises of several genes, i.e., each chromosome can be held as a string of several genes. The proposed GA generates an initial population of ten chromosomes in a search space and each chromosome is assigned nine genes such as orientation, intensity, scale etc. of a pixel in the image.

B. *Fitness Evaluation*

To select which individuals in the initial population will be favoured to breed to create the next generation, the fitness of every individual must be evaluated [24], [25]. The proposed GA evaluates the fitness (health) of each of the ten chromosomes in the context of suitable orientation in the initial population and arranges them in the ascending order of their fitness through a set of appropriate instructions incorporated in it.

C. *Selection*

In this step of the GA, two individuals depending upon their fitness calculated in the current population are selected as parents to breed a new generation of individuals [17], [23]. Roulette wheel selection and tournament selection are the two popular methods in this context but we implement a random selection method in the GA in which the fittest individual in the current generation and a randomly selected individual from the rest of the nine individuals will be selected to breed in

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order to reduce the selection time and adding diversity to the population in the solution space.

D. Reproduction

In the reproduction phase of the GA, the population of the next generation is created by implementing the two basic methods, cross-over and mutation [17], [25]. For every new child in the next generation, a pair of parents is selected from which the child inherits it's properties. In the GA proposed, we incorporate both the methods for reproducing the next generation.

E. Cross-over

The cross-over operator of the GA selects genes from the parent chromosomes and creates new offsprings [17], [23], [24]. The simplest way to realize cross-over is to randomly select a cross-over point (The locus position of a gene) and copy everything before this point from the first parent and after the cross-over point copy from the second parent. This is known as single point cross-over which results in two offsprings. Two points, multiple point and other cross-over techniques can also be used in GAs.

A single point cross-over technique is implemented in the proposed GA after allowing it to randomly select it's cross-over point so as to perform the mating of the two parents and exchange their genes across this point to create two new offsprings for the next generation.

F. Mutation

The purpose of the mutation is to enable the GA to explore new areas of the search space and prevents all the solutions in the population from falling in the local optima of the solution space by introducing and preserving genetic diversity [17], [25]. Mutation is incorporated in our GA for those chromosomes which are assigned the two lowest positions of fitness in every generation from the second generation onwards so as to preserve the best chromosomes having the highest fitness in every generation. The mutation of the best chromosomes in every generation is always advised against [23] and a very low percentage of the population in the generation should be mutated

V. SALIENT STEPS IN ALGORITHM FLOW

The salient steps in the sequence of the algorithm flow as can be observed from the flow chart of the GA shown in figure 2 are the following:

1. Randomly generate an initial population P of candidates, each having systematically selected an appropriate orientation value in addition to other genes.
2. Select an appropriate number of generations N.
3. For generations 1 to N do the following. // Main Loop.
   - 3.1 Evaluate the fitness of each candidate in the population P in the context of the appropriate orientation.
   - 3.2 Arrange the candidates in the ascending order of their fitness.
   - 3.3 If the generation limit has reached N then come out of the main loop and return the best fit candidate, otherwise proceed to the next step to create next generation.
   - 3.4 Create he next generation of candidates by following the steps a) to c)
     - a) Select the best fit candidate from P and randomly select the other candidate from (P-1) as parents for the cross-over.
     - b) Perform the single point cross-over after randomly selecting the cross-over point between the parents selected in the step a)
     - c) Replace the two lowest fit candidates in P with the two children from cross-over to create the next generation.
   - 3.5 Perform the mutation on one of the two randomly chosen child in the new population acquired in step c)
   - 3.6 Proceed to the step 3 above for the repetition of all the steps from 3.1 to3.5 with the new population

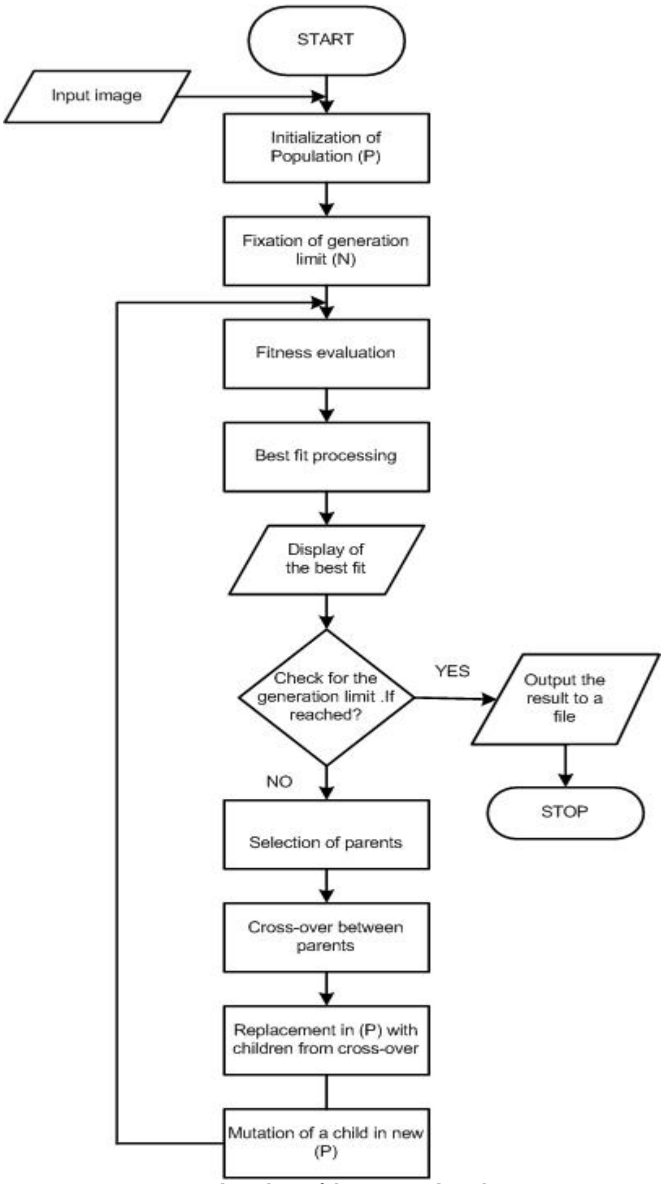

Fig. 2. Flow chart of the genetic algorithm.

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VI. Experimental Results and Performance Evaluation

A. Test Images

Images of the various industrial objects that are frequently employed in industrial work environment such as screwdriver, plier, adjustable spanner, open-ended spanner etc. are first captured with Sony's DSCW320 14MP digital camera under different light shades (colours) such as red, yellow, blue and white. Each object image is a JPEG image of 4320 X 3240 pixels resolution which is then resized and converted into BMP image of 100 X 100 pixels which reduces the cost of processing in terms of time and memory requirements multifold, since processing an image with a higher pixel resolution will consume more time and can prove to be quite a heavy burden on the memory [26].

Then in each such BMP image, the boundaries of the object are marked because of the various advantages associated with the use of markers in image segmentation [27]. It is used primarily to achieve gray-level segmentation using a single global threshold for the purpose of detecting the edges of the object and to take out any shadows and noise accompanying the object in the image and which can be caused due to the use of light in specific position. These BMP images are then submitted to the image database which contains 10 images only comprising of images of various industrial objects captured in different light shades. These images in the image database are used in experiments as the reference images by the genetic algorithm for the accurate estimation of orientation of the object of the same type in the test image given as input to the GA. The orientation of the object of a specific type in the reference image is taken to be equal to zero by the GA while processing the test image for accurate estimation of the orientation of the object of the same type in it. The image database is deliberately confined to a few images only instead of being made an expansive one owing to the ultimate objective to be realized in this work which is centered around the orientation estimation of the object in the image and not the detection of a particular object from a large pool of available objects of the different types in the image database. The purpose behind capturing the images of industrial objects in different light shades is to determine whether the GA design shows any sensitivity to the light colour in the process of estimation of object orientation since the real industrial environments are also sometimes exposed to the lights of different colours.

B. Performance and Results

Experiments were conducted using different images of the various industrial objects as the test images for the GA. The test images are of the same industrial objects whose images are kept in the image database but with different object orientations. These orientations of the specific degrees are induced in any chosen reference image kept in the image database by means of any appropriate software such as Corel photo-paint 10. The software incorporates the orientation of the desired degree in the chosen reference image thus inducing orientation of the same degree in the object with regard to its original position in the reference image. Due to the orientation induced, the corners of the chosen reference image are left fragmented white which are then filled with the colour to match as closely as possible with the colour of the reference image background to make the background of the test image consistently as close as possible with the background of the chosen reference image for the smooth and proper processing of the test image by the GA. This is precisely the reason for the presence of the fragmented corners which can be observed in all the test images shown in the figure 3. These test images are then provided as inputs to the GA in several experiments. It was observed that in most of the experiments, the GA behaved reliably well and performed as per expectations. It succeeded in providing a near accurate estimate of the orientation of the object in the test image. The orientation estimate of the object in the test image was arrived at by the GA by working in the counter clockwise direction from the original position of the object in the reference image. In these successful experiments, the GA was observed to arrive at the correct result by evolving less than half of the preset maximum number of generations.

In few experiments, the GA did not perform as per expectations and gave undesired results. In these experiments, it is observed after analysis that sometimes the GA was observed to get stuck on a test image with orientation already estimated in one of its last two or three runs. To overcome this problem, the GA was imparted a little training as a gentle reminder of its successful runs by making it to process those test images in which it arrived at near accurate orientation results so as to facilitate it to rediscover its course of arriving at correct orientation estimates. With this training, the GA was really able to turn around its performance in all these experiments.

In all the experiments conducted, the test images of various industrial objects captured in different light colours were used. It was observed that the various light colours did not have any effect on the performance of the GA in the accurate estimation of the object orientation.

The visual illustrations and results of the performance of the GA in six of the several experiments conducted with various industrial objects having different orientations are highlighted in figure 3. The test image column in figure 3 shows the test images of different industrial objects at different orientations captured in different light shades (colours) and used as input images for the GA in experiments. The reference image column in figure 3 highlights the reference orientation of the object of a specific type with regard to which the orientation of the object of the same type in the test images is estimated in the counter clockwise direction. The last two columns in figure 3 gives the value of the actual orientation induced in the object of the reference image and the orientation of the object estimated by the processing of the test image by the GA. The GA arrives at the appropriate orientation estimate of the object in the test image by processing the test image in the counter clock wise direction with regard to the object orientation in the reference image taken as the zero orientation value.

Reference Image	Test Image	Orientation (CCW*) Induced in Object in Degrees	Orientation (CCW) Estimated by GA WRT** Reference Image
		320	328
		150	153
		330	335
		190	197
		320	317
		50	44

Fig. 3. Visual illustrations and the results of the performance of the genetic algorithm.

*CCW - Counter clockwise **WRT - With regard to

VII. Conclusion and Future Scope

In this paper, efforts have been made to address the problem of orientation estimation of objects in industrial work environment using stand-alone GA and to evaluate its accuracy for the same. In the proposed methodology, the GA is designed to work in the stand alone mode taking complete charge of the problem relying solely on its evolutionary attributes to realize the objective of orientation estimation of objects. In its implementation in several experiments conducted as part of this evaluation, the GA design is observed to adapt quickly to come up with near accurate orientation estimates of various industrial objects (tools) of different shapes at varied degrees of orientations without any prior training and learning, shows immunity to the effects of various light colours red, blue, white and yellow used in the test images, converges to the optimal solution with a high degree of accuracy without requiring a high number of generations to evolve, say above 100. In a nutshell, this GA can be heralded as an adaptive, accurate and efficient in design and in its approach towards realizing orientation estimation accurately. But at the same time, it will be pertinent to mention that it also shows some functional constraints in a few cases where the need is felt for a little training as a reminder to the GA in order to enable it to rediscover the course well-treaded by it in its earlier runs towards correct orientation estimation.

The future work will be focussed on taking this design of GA and modifying it not only to iron out the little weaknesses it exhibited in a few cases but also for the accurate estimation of object localization and scale estimation based object detection. Attempts will also be made to address the problems of recognition of multiple objects in images based upon correct orientation and pose estimations, to detect and recognize overlapped objects in images centered around accurate orientation estimates of objects, to detect and recognize occluded objects in images. The GA will also be modified to address the problems of detection and recognition based upon accurate pose and orientation estimates in cluttered environments. The GA design in its current form can be taken to fuse with some other core technique which has a proven track record of reliability and efficiency to address the core problems in the aforementioned areas and allied areas as hybrid GAs have been observed to perform better and reliably well in most of these areas

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