ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

Pose Estimation in Automated Visual Inspection System using PSO

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Abstract

In this paper, we propose a Particle Swarm Optimization (PSO) based approach to determine the pose of a rigid body in Automated Visual Inspection having three degree of freedom. We have experienced the effect of noise at 20 dB SNR and 40 dB SNR and also observe mismatch getting from incorrect correspondence between object space points and image space points, on the estimation of three parameters. The maximum error in translation parameters (about x-axis and y-axis) is less than 0.1 cm and rotational error is less than 0.08 degree at 40 dB SNR and 0.45 cm and 0.6 degree at 20 dB SNR respectively. The error in parameter estimation is insignificant up to 5 pairs of mismatched points out of 16 points and results skyrockets when the mismatch occurs in more than 5 pair of points. These results have proved the robustness of PSO in determining the pose of object in automated visual inspection.

Keywords: Pose Estimation; Automated Inspection System(AVI); Particle Swarm Optimization(PSO)

Introduction

Inspection is an imperative piece of human beings.Inspection is particularly fundamental for the substantial industry e.g. Automobile industry to IC fabrication research center. Human himself can imagine everything by eyes and can measure everything more or less. In any case these sort of examinations are complex. It is moderate and puts a bottleneck to the fast rate of the large scale manufacture. It relies on singular's efficiency's. Automated Visual Inspection (AVI) redresses this week focuses of human. Not just it spares times and save the same exhausting work done by human, it can review in extremely productive way, can gauge such way, which is by unthinkable for people. What's more obviously it gives more flawless yield. It additionally spares the work expense of separate commercial ventures. Our Automated Visual Inspection framework based pose estimation problem can examine distinctive articles having less compelled positions. The blue-print of the object to be assessed is put away in the machine as a model. We endeavour to coordinate CAD-model with vision-based operations in investigation frameworks. We will attempt to get the ideal estimations of parameters from known picture space focuses what's more correspondence item space focuses.Automated Visual Inspection accommodates two terms: Automated demonstrate 6-pivot explained arm to perform a manual assignment naturally. Visual Inspection highlights the review of an object's surface to identify arbitrary surface deserts. AVI has been connected to an extensive variety of items. Because of the long set-up time for examination frameworks, AVI is suited to undertake where countless of the same sort are made in a creation nature's turf. Pose estimation in computer vision is felt in the zone of object recognition, where it is required for matching object models with one or more images, which are taken by machine controlled camera. Since fundamental goal is continually banging into precision of pose estimation under AVI framework. The arrangement of the pose estimation ought to be robust whether there are any manufacturing defects in the shape of the object or there is any mismatch between feature points of the object and images taken under observation.

Look into pose estimation that has been done with varied objectives and motivation. A far reaching overview of the early work at pose estimation can be found in Besl and Jain [3]. Haralick et. al. [1] introduce an answer for four pose estimation issues, to be specific 2-D to 2-D and 3-D to 3-D, 2-D point

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of view to 3-D pose estimation and 2-D perspective to 2-D pose estimation. The main focus is to demonstrate that least square method which can give robust solution in the event of mismatched pair matching. Abidi and Chandra [5] determine focal length of camera, intrinsic and extrinsic parameters of the target from the six measurement of a quadrangular target and image coordinates of each of its vertices. Christy and Horraud [12] presents a strategy for assessing the position and orientation of a camera regarding a known 3D object from line correspondences. The system needs to dodge the various arrangements and vigorously rely on upon the frail or perspective camera model.

Gold et. al. [8] gauges the pose from point matching. They take care of the two ways requirement issue utilizing softassign method rose up out of the repetitive neural system. Hati and Sengupta[4] present a system to discover pose estimation of a produced object in Automated Visual Inspection frameworks utilizing a progressive gathering of neural systems. They likewise demonstrated that traditional routines like minimum square, inclination procedures and others are not suitable for these sorts of issue because of immense non-linearlity. Hati et. al. [7] have demonstrated that GA-based strategy does not oblige managed adapting methodoliges as needed by manufactured neural system strategies, e.g. back propagation algorithm. GA advances progressively and can likewise stay informed concerning time differing procedures.PSO has a lot of advantages over other stochastic optimization techniques. PSO has no operators like crossover or mutation that are available in GA. It assumes simple algorithims. Only few parameters are updated in each generation. It is based solely on the movement of flying birds. Each flying bird, called particle, flies over the bounded search space. Elbeltagi et al. [13] compare the formulation and results of five evolutionary-based algorithms: GA, Memetic Algorithms, Particle Swarm Optimization, Ant Colony Optimization, Shuffled Frog Leaping. Based on this comparative analysis, they show that PSO method performs better than other algorithms in terms of success rate and solution quality and the processing time by PSO is quite well. PSO is robust in the sense of finding optimal solution in continuous optimization problems with uncertainty or fluctuations in the input variables or finding optima in dynamic environments or finding optima given noisy or uncertain objective functions. In view of this above, PSO based methods are applicable to finding optimum of multimodal functions.

In our work we have estimate the pose by registration of a sensed object model to a reference object model. This issue involves the dissimilarity between the models being registered and the accuracy of the registration. We have shown that the noise immunity power of PSO to outliers is far better than the robust method reported in literature. It can be designed to find near optimal solution out of huge search space.

Problem formulation

Let $x_1, x_2, \ldots \ldots \ldots, x_n$ be the n-vertices of the inspected model, in 3-D space. Under inspectionthe

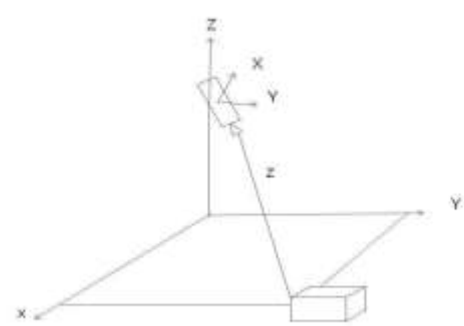

Fig.1: Schematic diagram of Automated Visual Inspection system. (X, Y, and Z) denote the 3-D Cartesian coordinate system. (x, y) denote coordinates of a pixel in image plane. Z is perpendicular to the image plane and (x, y) are parallel to image plane. So the free degree of movement is three, two is translation about X & Y axes and one is rotation about Z axis.

manufactured object is shifted with respect to defined position. Let (P_{i1}, P_{i2}) , $i = 1, \ldots \ldots \ldots, n$are the corresponding n-positions in image plane obtained by perspective projection at the manufactured object in its inspection position. The object space to image space relationship is given by,

$$P_{i1} = f \frac{r_1 x_i + t_1}{r_3 x_i + t_3} \ldots \ldots \ldots \ldots (1)$$

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$$P_{i2} = f\frac{r_2x_i + t_2}{r_3x_i + t_3} \ldots\ldots\ldots\ldots (2)$$

$$t = (t_1, t_2, t_3)'$$

$$R = \begin{pmatrix} r_1 \\ r_2 \\ r_3 \end{pmatrix}$$

Where ***t*** is the translation matrix, obtained in following steps,

Translation of a point with coordinates (X, Y, Z) to a new location by using displacement (X_0, Y_0, Z_0), such that

$$X^* = X + X_0 \ldots\ldots\ldots (3)$$

$$Y^* = Y + Y_0 \ldots\ldots\ldots (4)$$

$$Z^* = Z + Z_0 \ldots\ldots\ldots (5)$$

$$R = \begin{bmatrix} cos\theta & sin\theta & 0 & 0 \\ -sin\theta & cos\theta & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

f is the focal length of camera. As we stated before, there are three degree of freedom, two for translation about X and Y axes respectively, one for rotation about Z axis as in Fig. 1.

Let $(\Delta x,\ \Delta y, \Delta\theta)$ be the pose of inspected object, then equation 1 and 2 can be written as[6],

$$P_{i1} = f\frac{A\cos\alpha\ + B\sin\alpha}{-A\sin\alpha\sin\varphi + B\cos\alpha\sin\varphi - C\cos\varphi + f} \ldots (6)$$

$$P_{i2} = f\frac{-Asin\theta cos\varphi + Bcos\theta cos\varphi + Csin\varphi}{-A\sin\alpha\, sin\varphi + B\cos\alpha\, sin\varphi - Ccos\varphi + f} \ldots (7)$$

Where $A = (x_i + \Delta x - x_0), B = (y_i + \Delta y - y_0), C = (z_i + \Delta z - z_0)$ and $\alpha = (\theta + \Delta\theta)$.

The fitness function, a derivation of objective function can be constructed as, let Δx^e denote the estimation value of Δx at a iteration of PSO and similar in case of$\Delta y and \Delta\theta$. Now after translation and rotation of the given object by an amount of $(\Delta x^e,\ \Delta y^e,\ \Delta z^e)$. Let$(P_{i1}^e, P_{i2}^e\ ), i = 1, \ldots\ldots, n$ be the corresponding image points of the model after translation and rotation.

Let D be the distance function defined as,

$$D = \sum_{i=1}^{n}[\mathrm{Abs}\ (P_{i1}^e - P_{i1}) + \mathrm{Abs}\ (P_{i2}^e - P_{i2})] \ldots (8)$$

Where $Abs(x)$ denotes the absolute value of its argument x. Our objective is find the optimal values of $(\Delta x^e,\ \Delta y^e,\ \Delta z^e)$ such that D is minimum.PSO applies its particles to move in such way, so that D tends towards minimum.

Particle swarm optimization

PSO could be a Swarm Intelligence Technique however it contrasts from GAs. In PSO, there are not any DNA motivated operators applied on the swarm. The particles area unit assumed to fly inside the search area, A, iteratively. This is often potential by adjusting their position employing a correct position shift, known as velocity. Velocity is additionally updated supported by the data obtained in previous steps of the formula. This is often termed as memory. Memory store best position gained by each particles, known as fitness value.

PSO is predicated on simulation models of social behavior. Particles mutually communicate their experience with neighbour particles by an information exchange mechanism. The position comparable to the most effective fitness is understood as *pbest* and therefore the overall best is obtained from all the particles within the population, termed as *gbest* [9].

The featured of the looking out procedure are often summarized as follows [10, 11].

- Initial positions of pbest and gbest area unit are totally different. However, exploiting the various directions of pbest and gbest, all particles step by step get near the world minima or maxima.
- The changed values of the particles position area unit are continuous in nature.
- There's no inconsistency in looking out procedures notwithstanding continuous and separate state variables area unit used with

continuous axes and grids for XY positions and velocities.

If g_i denotes index of best particle (p) in neighbourhood then$p_{gi} = argminf(p_j)$. The changed rate and position of every particles are often calculated by exploitating the present rate and distance from the $pbest_{j,g} to gbest_g$as shown within the following equations [9]

$$V_{j,g}(t+1) = w * v_{j,g}(t) + c_1R_1\left(pbest_{j,g}(t) - x_{j,g}(t)\right) + c_2R_2\left(gbest_g(t) - x_{j,g}(t)\right) \ldots\ldots\ldots\ldots\ldots..(9)$$

$$x_{j,g}(t+1) = x_j, g(t) + v_{j,g}(t+1) \ldots (10)$$

Where $v_{j,g}(t+1)$ and $x_{j,g}(t+1)$ are the current velocity and position of particle i. $pbest_j$ and $gbest$ signify nearby best position and worldwide best position respectively. r_1, r_2 indicate random value uniformly distributed in the range (0, 1). $c_1 = c_2 = 2$ denote cognitive and social acceleration parameters. The inertia weight (ω) influences the union in PSO process. The computations are continue until objective value drops beneath the limit or the number of generations achieve the cutoff (Table 1).

Table 1
Parameter used for PSO algorithm in Pose Estimation problem

PSO parameters	Value/type
Swarm size	100
No. of iteration	500
c_1, c_2	2, 2
Initial inertia weight	0.9
Final inertia weight	0.4
Max. particle velocity	4

The known points on the object under inspection are generated using uniform distribution. The x, y and z coordinates of these points are chosen from the interval of [0, 400] randomly with uniform distribution such that these points are within viewing volume of the camera. The position and orientation is fixed at (0, 0, 200) and the pan of the x axis and tilt of the z axis is fixed at 120^0 both. Now, each points of the object will translate along x and y axes and will rotate about z axis. In this point we added identically distributed Gaussian noise N (0, σ) to every coordinate for each of these points. Signal to Noise Ratio (SNR) is defined as:

$$SNR = 20log\frac{10}{\sigma}dB$$

For the purpose of optimization of equation 8 as stated in chapter 3, routines from PSO are used. In our work the accuracy and fast convergence of PSO is essential, since it is real time inspection problem. Here for the whole swarm, the problem is of 3 dimensional. Each particle has three components, $\Delta x, \Delta y and \Delta\theta$. Thus three real number set together constitute the search space of PSO. Table 1 shows the specified parameters for the PSO algorithm.

For the very first execution of the program, a wider solution space is obtained and after then at every iterations, PSO tries to minimize the objective score as minimum as possible. Optimization is terminated by the pre-specified number of iterations. The optimization was performed with the total number of iteration set to 500.

Results and discussions

In this section we describe results of the computer experiments using synthetic data as wellas real data. We test the robustness and the performance of our algorithm using

I. 20dB and 40dB noise added to the actual data;
II. Number of control points in presence of noise;
III. Number of mismatched points in image space with those of object space inpresence of noise;

The pose parameters are varied and the results are obtained using Particle Swarm Optimization. The rangeof three parameters ($\Delta x, \Delta y, \Delta\theta$) are from -100 to 100 units. We care these values when the particles move over the search space for optimal result. In Fig 2 we show the result of computation experiments at 20 SNR as well as at 40 SNR. It is clear that error in translation is within 0.45 cm and rotational error is within 0.7 degree. We have increased the value of visible points of the solid under observation and marked improvement.

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
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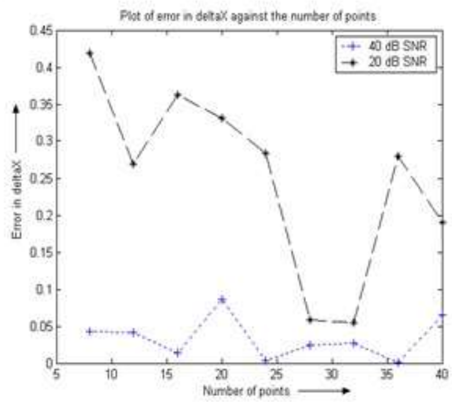
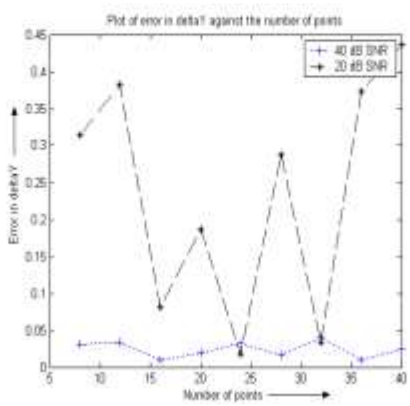
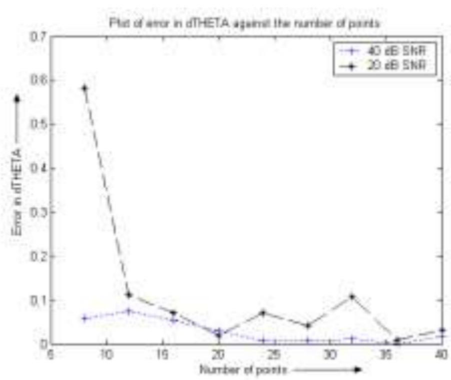


(a)



(b)



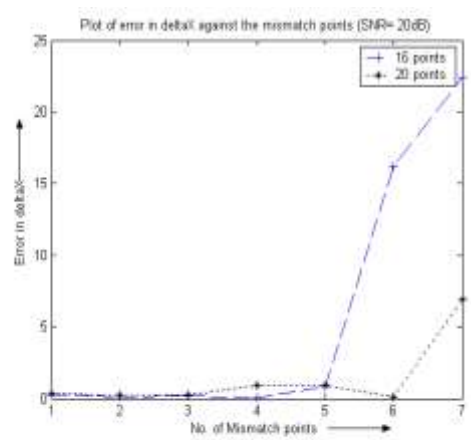
(c)

Fig. 2. The performance characteristics based on Particle Swarm Intelligence algorithm. Error in estimated three pose parameters $\Delta x, \Delta y, \Delta \theta$ areplotted separatelyagainst the number of points. In fig (a), (b) and (c) we compared magnitude of error against 20 dB and 40 dB SNR. Only magnitude is plotted.

Still nowwe are estimating pose of the object under observation has matching pairing between object points and image points. But in Fig. 3 we have shown the error in the estimation of parameters when mismatch occurs in the recognition of vertices of the object. We have done it through directly swapping between point's m and n, ($m \neq n$) in the image space. We have considered 16 points and 20 points and shown our results. The result show that PSO can determine pose of an object in Automated Visual Inspection system with high accuracy even there are lots of mismatch pairing. This shows, the robustness of PSO. However, the error skyrockets after a certain number of pair mismatching (5 pairs in case of 16 points and 6 pairs in case of 20 points).

In fig. 4 we have shown convergence characteristics of pose parameters with the presence of 20 dB SNR. In fig 4. (a) we have shown without no mismatching between object points and image points, pose parameters can converge very well. It is expected score. But in the presence of mismatching points, PSO can still converge the parameters very well. In fig. 4. (b) & (c) we have prove it.In each plot, the curve representingthe convergence characteristics of a parameteris labelled with the actual parameter value.

In fig. 5 we have plotted objective score (gBest value) of the best particle's position against the number of iteration. It is clear from the figure that



(a)

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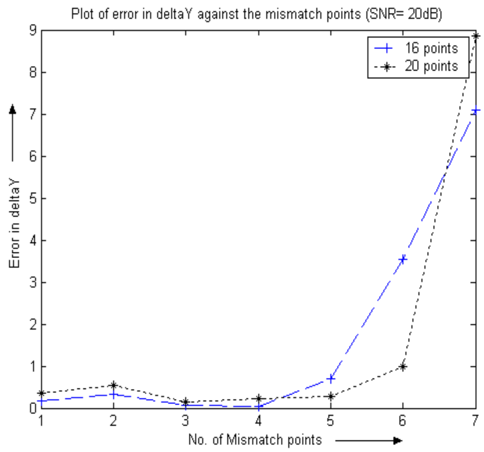
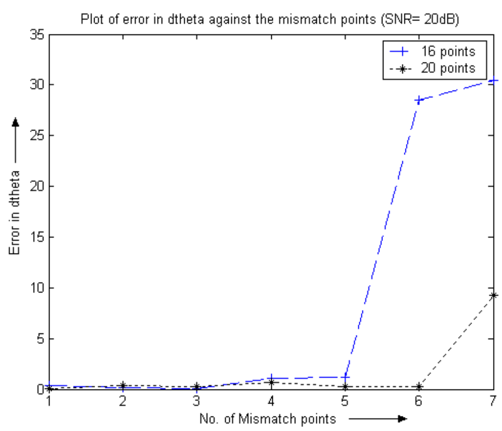
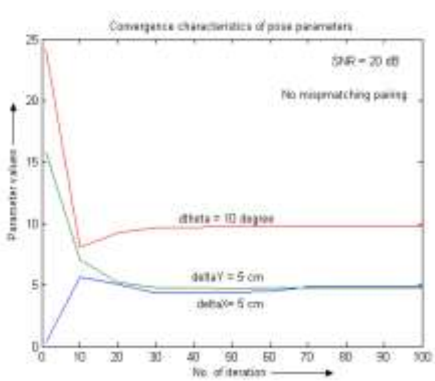


(b)

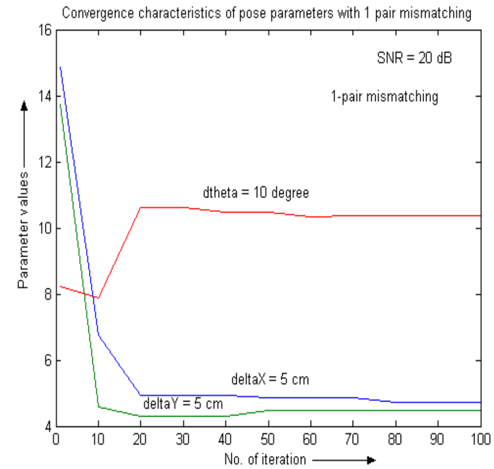


(c)

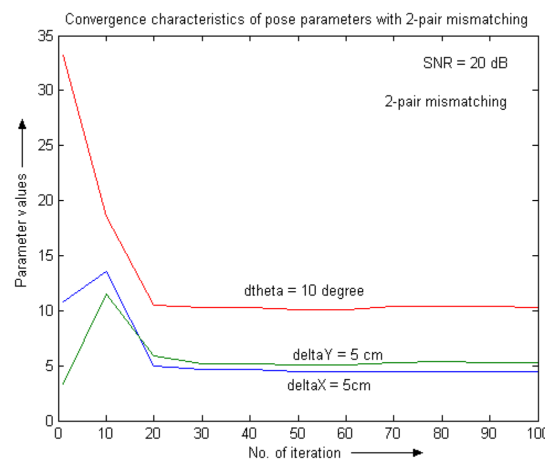
Fig. 3 Performance characteristics of PSO. Errors in three pose parameters are plotted against number of mismatch pairing. (a) deltaX and (b) deltaY are calculated in cm. and (c) dtheta in degree. Only magnitude of errors are shown here.



(a)



(b)



(c)

Fig. 4. Convergence characteristics of pose parameters, $\Delta x, \Delta y, \Delta\theta$ based on PSO under no mismatch and mismatch conditions. (a) plot without no mismatch pairing; (b) plot with 1-pair mismatch algorithm; (c)plot with 2-pair mismatch algorithm.

PSO converge within 20 iteration in case of no mismatch and one pair mismatch and 40 generation for two pair mismatching.

Experiments on Real Data

Here we have experienced our method on solid objects using QICAM FAST1394 digital CCD camera compatible with IEEE 1394 Firewall camera. We grab the image of models from different view points. For inspection of objects we keep it in predefined

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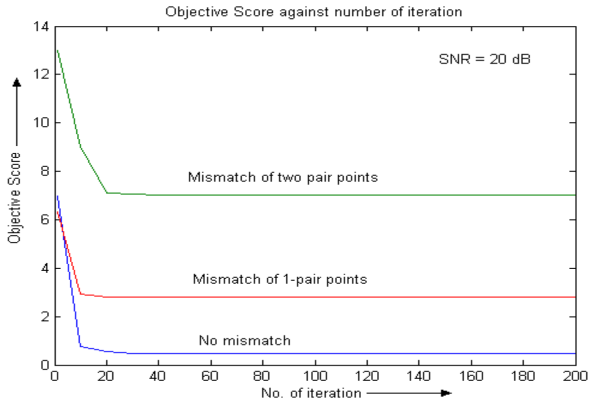

Fig. 5 Plot of objective value against number of iterations, without mismatch pairing and with mismatch pairing.

space. In Fig. 6, we have seen exact alignment of wireframe models of each objects with images of corresponding objects. This proves PSO is hearty and basic with few number of parameters to be balanced while seeking the solution.

Fig. 6 Allignment of wireframed models with the objects in real images.

Conclusion

In this paper we describe pose estimation from Automated Visual Inspection system with few number of control points. We have provided a flexible inspection system where objects have degree of freedom of movement. We have estimated three pose parameters using GA at 20 dB SNR. We have also performed our experiment on real objects and prove that PSO based method well enough to determine pose of objects in flexible inspection system.

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