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HYBRID METAHEURISTIC AND ITERATIVE APPROACH FOR AFFINE POINT CLOUD ALIGNMENT

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Abstract:

A three-dimensional alignment procedure is necessary to reconstruct a 3-D model. Although there are many methods for determining the rigid and affine transformation matrices of point sets, we are doing a seven-parameter affine transformation that includes scaling, translation, and rotation in this research. Therefore, we hybridize a metaheuristic Particle Swarm Optimization (PSO) algorithm for affine registration with the Iterative Closest Point (ICP) technique for further fine-tuning Point sets to construct a three-dimensional registration approach. Before applying the above algorithms, the point clouds are down-sampled by the voxelization process to reduce their density for a precise transformation. In this research, we have taken two datasets, i.e, Stanford Bunny and Stanford Tyra. To supply the transformation, we additionally alter these shapes. According to the results, with incredibly minimal registration mean squared errors(MSE) of 10^{-26} and 10^{-27}. The suggested approach may identify a very good transformation matrix for Bunny and Tyra's point clouds, respectively.

Keywords: Point Cloud Registration, Particle Swarm Optimization, ICP, MSE, Metaheuristic, Voxelization.

Introduction

Just like two-dimensional registration of point sets [1], 3D point set registration is necessary for certain other applications that need object form reconstruction following the registration procedure [2]. Examples of medical research projects [3] on three-dimensional picture registration can be found in [4]. Several features, such as point cloud coordinates that depict an object's three-dimensional shape, are used in the registration procedure in the aforementioned research projects. The registration procedure outlined in [5] has made use of these coordinates. A variant of particle swarm optimization (PSO) [6,7] [8] is used in all of the affirmed studies to identify the site that matches the target and source pictures. If there are simply rotations and/or translations, the majority of the current registration techniques locate the corresponding site or spots. However, there are other transform types, such as scaling and reflection, in the three-dimensional affine transformation. Therefore, we use the particle swarm optimization on 3D point cloud coordinates with the three-dimensional affine transform [9] to construct a registration algorithm. In this research, we used Particle Swarm Optimization [10] and, after that, we used the Iterative Closest Point hybrid algorithm [11, 12] on voxelized point clouds to make it a more accurate registration. Voxelization refers to the transformation of a three-dimensional model or point cloud into a collection of voxels—tiny

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volumetric units that serve as the 3D counterpart to 2D image pixels. This technique converts complex 3D forms, such as meshes or point clouds, into a structured voxel grid. Point clouds contain scattered points that don't follow any order, colour, smooth gradients or neatly arranged pixels. unlike traditional images, point clouds can be tricky to work with because they lack structure. Their spatial characteristics make them flexible. They can be rotated, scaled, and translated, but the uneven distribution of points across space adds complexity [13]. The voxel-based Iterative Closest Point(VICP) algorithm offers a refined approach to handle this. It builds on the standard ICP method by down-sampling the point cloud, converting it into a voxel grid. This makes it especially effective when the images or datasets are large, noisy, or misaligned [14]. In this study, we concentrate on three types of transformations: rotation, scaling, and translation on two datasets, i.e., Stanford Bunny and Stanford Tyra [32]. Reflection is left out, as it's rarely used in practical scenarios.

Literature Review

The Iterative Closest Point (ICP) algorithm remains popular because it is easy to implement and performs reliably. In areas such as 3D vision, robotics, and remote sensing, aligning point clouds is crucial since multiple sets of spatial data need to fit into a unified coordinate framework. However, the algorithm has challenges, particularly when the initial alignment is poor or when handling large datasets. It often gets stuck in local minima and can be inefficient for large scales [15]. "To tackle these problems, researchers have recently suggested metaheuristics [16, 17] and hybrid methods that combine optimisation techniques [18] like Particle Swarm Optimisation (PSO) with voxel-based pre-processing and ICP. These combinations seek to improve both accuracy and robustness. The ICP algorithm refines the transformation between point clouds by gradually reducing the distance between corresponding points. Its effectiveness heavily relies on a good starting position and struggles with noisy or incomplete input data [19]". Voxelization helps by breaking 3D space into evenly sized cubes or voxels. This approach simplifies down-sampling, reduces noise, and speeds up point matching. Filtering in this way has clear benefits for improving clarity and processing efficiency in point cloud tasks. PSO mimics how bird flocks move together and is a stochastic optimisation method that searches more broadly across transformation parameters. This feature allows it to avoid the local minima that often slow down gradient-based methods [3, 20]. PSO, which mimics the cooperative movement of bird flocks [21,22], is a stochastic optimization method that searches more broadly across transformation parameters. "ICP variations that utilise voxel grids streamline the early processing stages by compressing and cleaning the data, while also speeding up the search for matching points. Research indicates that combining voxel filtering with ICP provides a strong balance between precision and computational efficiency, especially with large or noisy datasets [11]. Typically, hybrid frameworks employ PSO to scan the transformation space globally for initial coarse alignment before using VICP for deeper refinement [23]. This two-phase approach reduces ICP's dependence on precise initialisation and helps it avoid local minima [24]. "Recent trends suggest that merging voxel filtering, PSO, and ICP is a promising way to enhance registration outcomes. Voxel-based noise reduction and down-sampling are essential for minimising data volume and removing irrelevant information". Effective pre-processing of point cloud data enables robust optimization. For global optimisation, PSO explores the transformation space to find the best parameters and helps address issues related to poor initial alignment [20] [21]. In the local refinement stage, the Iterative Closest Point (ICP) algorithm, potentially enhanced through voxelization, adjusts the alignment with greater precision to achieve accurate registration. Such hybrid frameworks have demonstrated improved accuracy, robustness to noise, and computational efficiency, particularly in scenarios involving large-scale or partially overlapping point clouds. Feature-Based Enhancements: Some studies incorporate feature descriptors (e.g., SHOT, FPFH) with voxel filtering to improve correspondence accuracy before applying PSO and ICP [25]. Hierarchical and Multi-Scale Strategies: Multi-scale voxelization and hierarchical optimization have been proposed to further balance accuracy and efficiency, especially for complex or multi-resolution datasets [26]. Deep Learning Integration: While deep learning approaches are gaining traction, hybrid optimization methods remain highly relevant for scenarios where data-driven models are less practical or interpretable [27]. Hybridizing PSO with voxel-based ICP leverages the strengths of both global and local optimization, addressing key limitations of traditional ICP in point cloud registration, i.e, point to point or point to plane [28]. This approach is particularly effective for large, noisy, or misaligned datasets, and ongoing research continues to refine these methods with advanced feature extraction, multi-scale processing, and integration with learning-based techniques [7, 23].

Registration Method

By determining the optimal transform matrix between the two point cloud pictures utilized in the three-dimensional registration, the best matching site may be found:

$$\mathbf{T}^* = \arg\min O\left(\mathbf{T}(\mathbf{B}), \mathbf{A}\right)$$

Where the target and source point clouds are denoted by $B([b_i]M\times4)$, M denotes the number of target cloud points, and $A\ ([a_j]\ N\times4)$, N denotes the number of source cloud points. T denotes a geometric transformation estimated by finding the nearest neighbour between a set of point pairs (a_j, b_j). $O(\,.)$ is the Objective function. The mean square error(MSE) is found after the minimum error of distance between the two points is taken. The calculation of the mean square is shown in equations (2) and (3).

$$\mathbf{T}^* = \arg\min_{\mathbf{T}} \frac{1}{N} \sum_{j=1}^{N} \left(\mathbf{b}_j \cdot \mathbf{T}^t - \mathbf{a}_j\right)^2, \tag{2}$$

$$\mathbf{a}_j = \arg\min_{a_i \in \mathbf{A}} \left\|\mathbf{b}_j \cdot \mathbf{T}^t - \mathbf{a}_i\right\|. \tag{3}$$

The three-dimensional transformation [29] with seven parameters, i., 3 parameters for translation, 3 parameters for rotation, and one parameter for scaling. After completion of initial affine registration by PSO, we will use ICP for another fine-tune of the registration process to cut the computational cost, because if we use only PSO, then a larger number of iterations are required for the best registration. Parameters are arranged in a matrix as follows.

$$T = R * S + t \tag{4}$$

$$\mathbf{T} = \begin{bmatrix} SR11 & SR12 & SR13 & t_x \\ SR21 & SR22 & SR23 & t_y \\ SR31 & SR32 & SR33 & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5}$$

The non-rigid transformation in *S*R* form for the top left 3X3 block parameters, SR11 to SR33, are represented by the rotation matrix R and the uniform scaling factor s.” *tx, ty*, and *tz*”, on the other hand, indicate the translation vector. Homogeneous coordinates, fixed at [0, 0, 0, 1], are present in the bottom row of the matrix to facilitate matrix-vector multiplication in homogeneous space. The scaling factor ensures that the parameter "s" varies from 0.8 to 1.1. How the parameters used to create an affine registration are displayed in the matrix below.

$$T = \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \tag{6}$$

$$T* = \begin{bmatrix} s(r_{11}x + r_{12}y + r_{13}z) + t_x \\ s(r_{21}x + r_{22}y + r_{23}z) + t_y \\ s(r_{31}x + r_{32}y + r_{33}z) + t_z \\ 1 \end{bmatrix} \tag{7}$$

To find the optimal transformation, particle swarm optimization is used. Each particle of the population has seven dimensions. Personal best is found from each i^th^ particle and global best is found from the set of particles, i.e., swarm or population, let X = {x*j* |j = 1....N}. Here, the set of particles represents the set of solutions. The values set for the parameters for the transformation process are given below.

Table 1: Parameter boundaries for registration

parameter	symbol	lower bound	upper bound
Translation	tx,ty,tz	-6	+6
Rotation	$\theta x, \theta y, \theta z$	-180	+180
Scaling	Sx,Sy,Sz	0.8	1.1

Equations for velocity and position updating equations are given below.

$$v_i^{(t+1)} = w \cdot v_i^{(t)} + c_1 \cdot r_1 \cdot (pbest_i - x_i^{(t)}) + c_2 \cdot r_2 \cdot (gbest - x_i^{(t)}) \tag{8}$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \tag{9}$$

velocity of particle *i* at time *t* denoted as V_i(t), position of particle *i* at time *t* denoted as *xi*(*t*), pi ^{best}: personal best position of particle *I* denoted as pi ^{best}, best global position among all particles denoted as g^{best}, w stands for inertia weight (controls momentum), c1, c2 stands for acceleration coefficients for cognitive and social components respectively. r1, r2 are random numbers in the range 0 to 1. After the affine transformation by PSO, further fine-tuning of registration is done by the ICP algorithm by applying rotation and translation only. The improved ICP algorithm of this paper uses the K-tree method [30], which speeds up the process of discovering corresponding points and removes point pairs that exceed a certain threshold for valid registration based on Euclidean distance. The K-tree nearest neighbour method finds the points Kj that are closest to the source point Ai, cloud A, and correspond to the target point cloud Bi. A specified threshold is used to compare the average Euclidean distance between Ai and Kj. If the average value exceeds the threshold, this point will be removed. Out of all the points in the target, the corresponding point Ai with the minimum Euclidean distance from Kj will be identified if the mean value is less than the threshold. Fitness function [31] for PSO and ICP algorithm are given in equations (10) and (11) as follows.

$$f(\mathrm{x}) = \sum_{i=1}^{N} \|SR\mathrm{p}_i + \mathrm{t} + H\mathrm{a}_i - \mathrm{b}_i\|^2 \qquad (10)$$

$$E(R,t) = \min_{R,t} \sum_{i=1}^{N} \|b_i - (Ra_i + t)\|^2 \qquad (11)$$

Summarization of the Proposed Algorithm used for Affine Point Set Registration is as follows

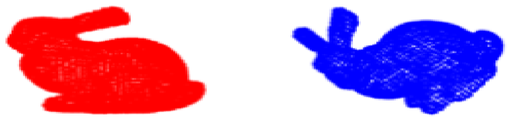
- Down Sample the Datasets
- Perform PSO on the Voxelised Data sets
- For each Iteration
    - For each Population
        - Update the velocity of each particle using equation (8)
        - Update particles position using equation (9)
        - Update each particle's best (local best)
        - Update the global best(Gbest)
    - End For

  End For
- Perform ICP on the Aligned point sets for further fine Transformation

Experimental Results

We have taken the original two datasets [28] as target point clouds and transformed them to differentiate between the source and target. We have tuned the parameters of the PSO algorithm to find the best parameter set to give optimal fitness value and avoid local optima by using the maximum search space. The original matrix for transformation is as follows:

$$T = \begin{bmatrix} -0.3345 & -0.1732 & 0.7673 & 3.9620 \\ 0.7136 & 0.2838 & 0.3752 & -0.9926 \\ -0.3308 & 0.77874 & 0.0326 & -5.9370 \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad (11)$$



Target Point Cloud(Bunny) Source Point Cloud(Bunny)

Target Point Cloud(Tyra) Source Point Cloud(Tyra)

Figure 1: SOURCE AND TARGET POINT CLOUDS OF BUNNY AND TYRA

Values set for parameters of PSO algorithm are given in the table(2).

Table 2: Parameter Boundaries For Registration

Parameter	**Symbol**	**Values**
Particle	x	200
Iteration	I	400
Inertia Weight	w	0.7
Personal Learning Coefficient	C_1	1.4
Global Learning Coefficient	C_2	1.4

Affine matrix for Bunny dataset after registration

$$T = \begin{bmatrix} 0.6363 & -0.6363 & 8.9795e-12 & 0.3000 \\ 0.6363 & 0.63632 & 2.57233e-11 & -0.2000 \\ -2.4538e-11 & -1.1839e-11 & 0.9000 & 0.0999 \\ 0.0 & 0.0 & 0.0 & 1.0 \end{bmatrix} \tag{12}$$

Affine matrix for TYra dataset after registration

$$T = \begin{bmatrix} 0.4500 & -0.1318 & 0.7681 & 0.2999 \\ 0.4499 & 0.7681 & -0.1318 & -0.2000 \\ -0.6363 & 0.4499 & 0.4500 & 0.0999 \\ 0.0 & 0.0 & 0.0 & 1.0 \end{bmatrix} \tag{13}$$

Optimizing PSO means balancing computing time and memory space based on problem scale and resources. In the case of PSO, global search and high accuracy require more space and time. Here in this research, we have taken population size from low to high for the same number of iterations for 2 different datasets of different sizes. It has been found that when population size increases, it improves search quality or exploration for the same number of iterations.

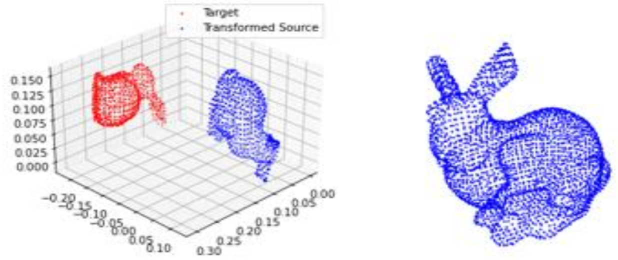
Table 3: MSE On Varying Swarm Size

Population size	**No of Iterations**	**MSE(BUNNY)**	**MSE(tyra)**
50	400	8.792^{-05}	4.229^{-05}
100	400	8.023^{-09}	4.395^{-13}
150	400	5.027^{-16}	2.654^{-20}
200	400	3.850^{-23}	5.478^{-26}
250	400	1.240^{-23}	2.218^{-26}
300	400	3.816^{-24}	4.268^{-27}

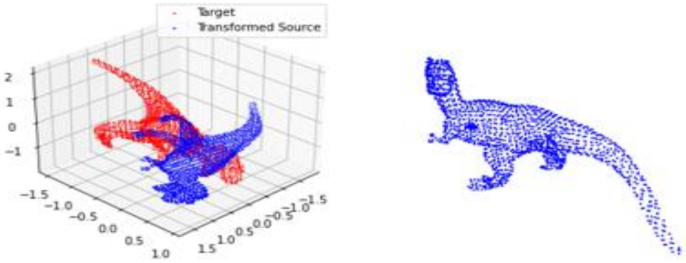
Recent experimental results (as presented in Table 4) highlight the final Mean Squared Error (MSE) values obtained through the implementation of both the standard Particle Swarm Optimization (PSO) and the enhanced PSO integrated with the Iterative Closest Point (ICP) algorithm. Furthermore, Figure 3 illustrates the progression of MSE across iterations for both datasets. These findings consistently indicate that the proposed PSO-ICP hybrid approach for affine registration demonstrates superior convergence behaviour compared to the conventional PSO method, thereby validating its effectiveness across diverse dataset conditions.

Table 4: MSE Registration Of Datasets

Data Set	MSE(PSO)	MSE(PSO+ICP)
BUNNY	6.233^{-24}	2.884^{-26}
TYRA	5.392^{-26}	1.953^{-27}



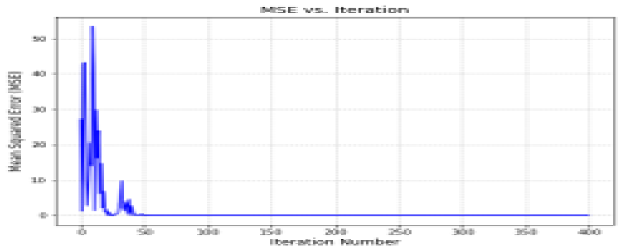
Before registration(Bunny) After registration(Bunny)



Before Registration(Tyra) After Registration(Tyra)

Figure 2: BEST CONVERGENCE RESULTS OF TWO DATASETS

MSE Convergence Graph(Bunny)



MSE Convergence Graph(Tyra)

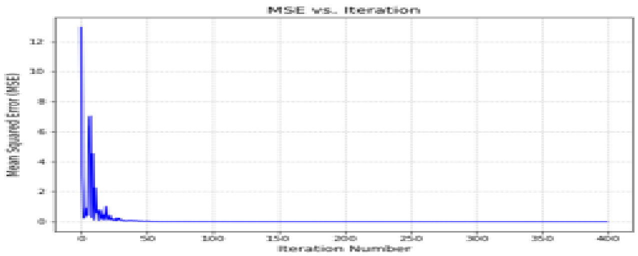


Figure 3: MSE OF THE OPTIMIZATION PROCESS OF BUNNY AND TYRA

Conclusion

Three-dimensional registration plays a vital role in reconstructing 3d models across various domains, particularly in medical and health care fields like orthodontics, orthopaedics. Several modern three-dimensional registration methods rely on swarm intelligence to optimize parameter selection. However, these approaches typically fall short when it comes to performing transformations that involve scaling, rotation, and translation. To get an accurate alignment result, traditional ICP algorithms need a high level of initial point cloud position. When the initial positions of two point clouds differ greatly, the alignment process tends to be slow, often getting trapped in a local optimum and requiring considerable time to converge. To address the issues of PSO and ICP techniques mentioned above, we provide a particle swarm optimization-based alignment technique for affine registration in addition to an enhanced ICP algorithm for further fine-tuning. The final alignment of the point clouds is achieved by swiftly matching corresponding point pairs through an improved ICP algorithm that utilises a K-tree structure and a distance threshold, while discarding mismatches. Experimental results evaluating convergence speed, processing time, and alignment precision show that voxelized PSO with ICP can identify a suitable transformation matrix with remarkably minimal registration mean squared errors(MSE) of 10^{-26} and 10^{-27}. Future research may incorporate supplementary methods to enhance the transformation process and refine the final output.

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