A 3D Matching Method to Compare a Scan to Its Reference using 3D Registration and Monte Carlo Metropolis Hastings Optimization for Industrial Inspection Applications

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Abstract: Currently in industry, inspection tasks are essential to ensure a product efficacity and reliability. Some automated tools to inspect, i.e. to detect defect exist, but they are not adapted to an industrial inspection application. Most of industrial inspection is human made. In this article, we propose a new algorithm to match a 3D point-cloud to its 3D reference to track visual defects. First, we reconstruct a 3D model of an object using Iterative Closest Points (ICP) algorithm. Then, we propose an ICP initialization based on a Monte Carlo Metropolis-Hasting optimization to match a partial point-cloud to its model. We applied our algorithm to the data measured from a Time-of-Flight sensor and a RGB camera. We present the results and performance of this approach for objects of different complexities and sizes. The proposed methodology shows good results and adaptability compared to a state-of-the-art method called Go-ICP.

1 INTRODUCTION

Today in industry, inspection remains a complex and hard task to achieve for an operator. Most of its activity is done by eye, sometimes in hostile or dark environment e.g., in a wind turbine nacelle or in a pipe system for energy distribution. Automatize part of their task with computer vision or Artificial Intelligence (AI) will help make their work less difficult. Such technology assistance should answer to ground reality of the inspection work:

- These methods must be applicable in real time. The operator needs the result during its inspection cycle to buy replacement parts.
- These approaches must be precise. In some fields like aeronautics.
- These solutions require to treat any object size. In aeronautics, the operator inspects objects from a bolt to a turbine.

Online drones, robots or other platforms equipped with sensors can be used to recover data on the condition of the object. W. Chen et al., 2020 studied the state of power lines using a drone using a deep learning (DL) approach to classify foreign objects. Saavedra et al., 2021 also used a DL approach for analyzing X-Ray images. Overall, classification and object detection are essentially based on Machine Learning (ML) technics. However, these methods efficiency depends on the training database, its diversity and size. For industrial inspection, this will imply a large training database for each inspection application. Yet, to our knowledge, there is no public database for industrial inspection.

Instead of using ML approach, a well-known approach consists in comparing a scan of the object of interest with its no-defect 3D reference. For example, in Abdallah et al., 2020; Abdallah et al., 2019, they used Computer-aided design (CAD) as the no-defect reference. Such approach needs CAD, which is not always available in industry, especially in aeronautics where pieces are often replaced by new models.

In this work, we present our method to compare an object 3D scans with its reference model to detect defects. Our goal is to provide an approach fitting the inspection requirements. Our approach can provide a

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3D model of the object to have a standard reference, which means it does not require CADs.

2 RELATED WORK

In this section, we briefly introduce state-of-the-art methods for evaluate changes between a 3D model and a partial scan of an object. First, we present methods creating a 3D model in a section called 3D reconstruction. Then, we present several methods to evaluate changes on the object, i.e., 3D matching. Finally, we will present some optimization methods to improve 3D matching.

2.1 3D Reconstruction

The literature shows that 3D reconstruction is a common problem. There is two main approaches studied: photogrammetry (Bhadrakom, 2016) and point cloud processing (Bethencourt & Jaulin, 2013). The first category reconstructs 3D models using set of 2D images and camera information via Structure from Motion to produce point cloud. Points of interest are extracted using Scale-invariant Feature Transform (SIFT). The second category, called point cloud processing, is mainly based on merging partial point clouds using 3D matching algorithm (Bethencourt & Jaulin, 2013). Partial point clouds are usually pre-matched using interest points extractor like SIFT. Then, Random Sampling Consensus (RANSAC) (Zhou et al., 2016) is applied to get a first point cloud alignment. Finally an Iterative Closest Point (ICP) (Besl & McKay, 1992) step refines the alignment estimation. If available, pose estimation can be improved using Inertial Measurement Unit (IMU).

However, these methods are not suited for inspection application mostly due to the lack of precision for photogrammetry, lack of data for ML approaches, and due to the time cost and adaptability for existing 3D matching method. To resolve this issue, we have chosen a simple method. It is based on existing tools of 3D reconstruction, allowing to obtain a 3D model of an object under few minutes with a precision around 1mm. A set of 3D scans are fused to reconstruct an object based on ICP color (Park et al., 2017).

2.2 3D Matching

A wide range of algorithms exists for matching two point-clouds. Each of them has advantages and limitations. We can cite for example RANSAC combined with Fast Point Feature Histogram (FPFH) (Rusu et al., 2009) or Kernel correlation (KC) (Tsin & Kanade, 2004). However, these approaches suffer from intrinsic limitations such as the high computational cost for the most precise ones, or the non-uniqueness of the minimization solution due to the high dimensionality problem. Iterative Closest Point is the widest and commonly used method for registration (Wang & Zhao, 2017) due to its fitness and precision. They are many studies to optimize and to improve ICP (Lamine Tazir et al., 2018; Park et al., 2017; Pomerleau et al., 2015). This method consists in minimizing the following criterion:

$$\chi^2 = \sum_{i=0}^{N} \left\| \vec{p}_i' - \left(\hat{R}\vec{p}_i + \vec{t} \right) \right\|^2 \tag{1}$$

where $\vec{p}_i'$ is the position of the target point cloud, $\vec{p}_i$ is the corresponding points in the source point cloud, $\hat{R}$ is a rotation matrix and $\vec{t}$ a translation vector. A k-Nearest Neighbors (k-NN) algorithm evaluates the pairwise similarity. As shown in the previous equation, ICP is a self-consistent method which requires to initialize some parameters. Due to the high dimensionality of the equation to minimize, local minima can occur. However, adding constraints to the problem can help with this issue. We present three commonly used ICP approaches:

- ICP point-to-point (Pt to Pt) (Arun et al., 1987): This is the initial approach developed. It is used as base for every ICPs variants.
- ICP point-to-plan (Pt to Pl) (Besl & McKay, 1992): This variant add surface constrain to equation (1).
- ICP color (Park et al., 2017): Based on ICP Pt to Pl, this variant add the RGB information of the point cloud as another constrain in the minimization equation.

However, such methods alone require an a priori to be executed. This implies or to have two scans with an initial important overlap, or to have an approximated form of the transformation matrix. To define the most suited ICP approach for our problem, a preliminary study was performed on complex object as a pipeline system. Results for scans matching show better results for ICP color in term of precision and overlap between two scans. Color information add a degree of freedom that help to get optimal 3D matching. So, we applied ICP color to generate the 3D models used as reference for the object inspection.

2.3 Global Optimization

As we said in the section before, ICP and generally 3D matching methods are sensitive to initialization.

They are not sufficient to match points in any cases since these methods can converge to local minima. A common approach is to use global optimization for initialization (Linh & Hiroshi, 2015; Yang et al., 2016). The literature shows different methods. First category being deterministic optimization methods. These methods use rigorous optimization providing a theoretical guarantee to find the best solution. We can cite Bound and Branch (BnB) as an example of such approach (Land & Doig, 2010). Yang et al., 2016 proposed an algorithm that make use of BnB combined with ICP to find global optimal matching called Go-ICP. In such method, a rough optimization is done using BnB approach, followed by a fined ICP optimization. The BnB and ICP procedure is repeated until convergence is reached. However, these methods are computationally expensive since they explore recursively all the possibilities to get the global minimum. Second category is stochastic optimization. A well-known example is Monte-Carlo based simulation. These methods use randomness to explore all the solution and retain only the best one. They are easy to implement but require important computational time to guarantee the optimal solution. The last category is metaheuristic optimization methods based on iterative stochastic algorithms. They use random sampling to extract information of a given cost function local properties. These methods allow to get optimal solution but do not assure to find the optimal solution. Linh & Hiroshi, 2015 proposed an approach based on simulating annealing (van Laarhoven & Aarts, 1987) combined with ICP to do point cloud matching. Their procedure is similar to Go-ICP procedure in which a simulated annealing is done instead of BnB. Such approach is not suited due to possible slow convergence and high risk to be stuck in local solution for symmetric object and/or plan.

For this work, we used a metaheuristic method of optimization refer as Monte Carlo Metropolis Hastings (MCMH) (Hastings, 1970). This method based on the Markov chain is simple to adapt to our problem. However, such methods are limited alone because finding the best matching solution would be expensive in time cost. In the next section, we explain our approach which uses MCMH to find an approximate solution before refinement with ICP.

3 3D MATCHING APPROACH

In this work, we propose a new complete approach to detect defects by comparing a generated 3D model with a partial scan. Figure 1 shows the proposed approach based on 3D registration with ICP and global optimization. First, we apply preprocessing on point clouds to clean it. Then a first 3D matching evaluation is done using MCMH. The 3D matching is refined with a last ICP color (Park et al., 2017) calculation. Our solution gives as output a comparison between the scan and the reference 3D model.

In a first part, we will present the pre-processing in which we present cleaning steps of scans before matching. Then, we will present our matching method based on MCMH combined with ICP color.

3.1 Pre-process

Scans are cleaned before 3D matching due to possible outliers created by the sensor used for scan capture. Cleaning process stands in three steps. First, we remove the background. Above a certain distance, the sensor suffers from distortion in the measurement. Given the a priori of working on a close-by object, we remove points with a depth over a threshold dependent of the sensor range sensibility. Secondly, if the object is placed on a surface, we remove the surface. RANSAC is used to estimate plan equation and to remove points from and below the plan. Thirdly, we apply a statistical outlier removal method to remove points considered as noise. We also use clustering method (Ester et al., 1996) to highlight cluster of points and discriminate clusters having less points than an empirically defined threshold (~ 500 points). This allows to only keep the points of the object of interest.

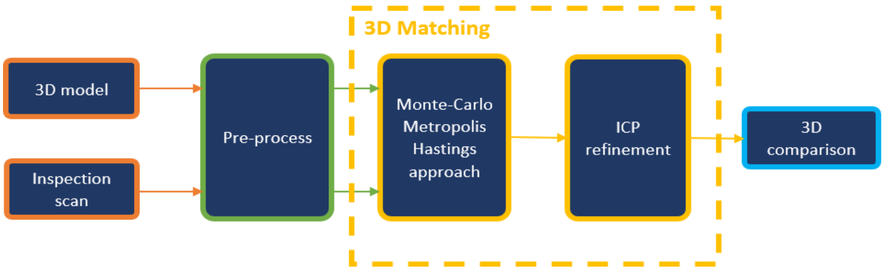

Figure 1: Scheme of the 3D matching process of our developed approach. We focus in this article on the 3D matching.

3.2 Scan Matching

We know ICP requires a good initialization to have good results due to its self-consistent nature (cf. equation (1)). That is why, usually, ICP methods are used as a last step for fine registration. To solve our matching problem, we need a global 3D matching approach. We show in the related work section that the optimization field helps to find a global optimal solution. We present here our approach based on MCMH combined with ICP to match a misoriented scan to its 3D reference. We also compare our method to Go-ICP (Yang et al., 2016) a state-of-the-art method. Since this last method is based on a deterministic approach, we assume it should find correct solution, and so it can be used as a comparison.

3.2.1 Monte-Carlo Metropolis Hastings

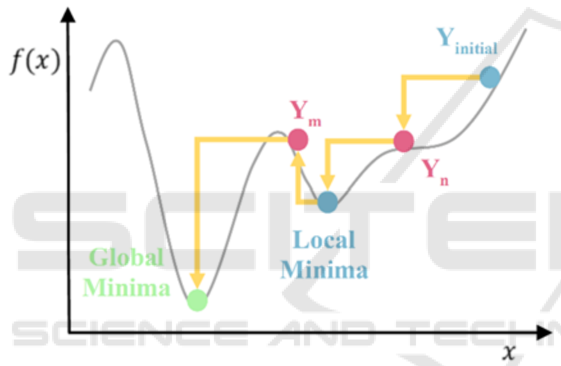

Figure 2: Scheme of the MCMH exploration. MCMH allows to overcome barrier to find global minima.

As the previous section explains it, MCMH approach is a meta-heuristic method used for phase spaces exploration and optimization of cost function. In our case, phase space corresponds to translation and rotation spaces to apply on the scan point cloud to match the 3D model point cloud. The Figure 2 illustrates the approach. Rotation and translation are initialized with given values ($Y_{initial}$ in Figure 2). Rotation matrix expression is derived from Euler angle. Then, we apply random variation on rotation angles and translation elements. A new transformation is then evaluated (Y_n in Figure 2). If the new obtained configuration minimizes the overlap between the two points clouds, then the solution is set as the new reference. Else, in a classical Monte-Carlo Markov Chain (MCMC) simulation, the solution is rejected. However, in MCMH an acceptance criterion is added: The Metropolis-Hastings criteria. It is the probability of transition between the previous and the new estimated values of the cost function. Usually, the probability is expressed as follow:

$$p_{trans} = \exp\left(\left(f(x_{iter}) - f(x_{ref})\right) * \beta\right) \quad (2)$$

With β the inverse of a fictitious temperature. A uniformly random number is drawn. If the random number is lower to the computed probability of transition, then the new state is kept (as shown with the kept solution Y_m in the Figure 2). Else the state is finally rejected. This procedure allows to exit local minimum and to overcome barrier in the phase space. A new random variation is drawn at each iteration. This procedure allows to access the global minima.

3.2.2 Hungarian Distance Criteria

To compute a cost function expressing the similarity between two point clouds, we use pairwise Euclidian distance between source and target. We compute a cost matrix which is optimized using the Hungarian algorithm (Kuhn, 1955). The diagonal of the cost matrix corresponds to the smallest pairwise distance between the two considered points clouds. The MCMH will optimize the value of the cost matrix trace.

First, cost matrix between points of source and target is evaluated. Then, we execute the Hungarian algorithm to solve the assignment problem. Concretely, solving the problem consists in performing permutation operation on the cost matrix to minimize its trace. Each of the diagonal elements corresponds to the scan and source optimal pairwise. We compute the trace and divide the value by the number of diagonal elements. We refer to this value as the average Hungarian distance in the rest of this article. The following equation present the equation to minimize:

Figure 3: Photo of the lego and pipeline systems used for our tests.

$$D_{hung,0} = \frac{1}{N_{diag}} \min_{L,R} Tr\left(\hat{L}\hat{C}\hat{R}\right) \tag{3}$$

Where $D_{hung,0}$ is the average Hungarian distance we seek to minimize, N_{diag} is the number of diagonal elements of the cost matrix $\hat{C}$, and $\hat{L}$ and $\hat{R}$ are respectively line and row permutation matrix. With the MCMH, we seek to minimize this value by applying variations on rotation and translation.

3.2.3 Our Matching Algorithm

We present below a pseudo-algorithm which explain the global matching procedure of our approach.

Pseudo-algorithm 1: Our approach based on MCMH optimization procedure.

Input: Scan point cloud **S** and 3D reference model point cloud **M**
Output: Optimal transformation $\hat{\mathbf{T}}$ of **S** to **M**
1: Compute topological descriptor of **S** and **M**
→ **S'** and **M'**
2: Align the center of mass of **S'** and **M'**
3: Compute the initial average Hungarian distance D_{hung}
4: Initialize the rotation and translation
5: MCMH algorithm
→ Best approximate transformation $\hat{\mathbf{T}}_0$, $D_{hung,0}$
6: Rotation of 180° on Oy axis of **S'**
7: Perform the same described procedure between line 2 and 5
→ Best approximated transformation $\hat{\mathbf{T}}_1$, $D_{hung,1}$
8: **if** $D_{hung,0} > D_{hung,1}$ **then**:
9: | $\hat{\mathbf{T}}_0 = \hat{\mathbf{T}}_1$
10: ICP color evaluation based on $\hat{\mathbf{T}}_0$ → Compute $\hat{\mathbf{T}}$
11: **return** $\hat{\mathbf{T}}$

In step 1 of our method, topological descriptor corresponds to a simplified triangular mesh. Point clouds are converted into triangular mesh using Poisson surface reconstruction of Kazhdan et al., 2006. Simplification of triangular mesh uses voxel downsampling on vertices. Then we have a simplified shape of the original point cloud. Vertices from this shape are used for cost matrix evaluation. This step is important to reduce computation cost.

First MCMH is computed, followed by a second MCMH on the same scan rotated by 180° on the Oy axis. The choice of the Oy axis is motivated by the idea that the object is placed on a surface. This change of initial point allows to begin the MCMH procedure to a different place in the phase space and so, to access a different path to the global solution. This second MCMH helps to overcome similarity problem (like in quasi-symmetric systems).

Table 1: Matching results for the model of lego with our MCMH approach.

	Matching time (s)	Success rate (%)	RMSE (mm)	Fitness (%)
Scan 1	13.1 ± 1.4	65.5	0.73 ± 0.04	83.1 ± 1.1
Scan 2	13.2 ± 0.6	71.5	0.66 ± 0.04	91.3 ± 2.3

4 TESTS AND PERFORMANCES

4.1 Technical Settings

Calculations and tests are done on a Mac OS computer with Intel® Core™ i9 with 8 cores, a frequency of 2.3 GHz and a RAM of 16 Go. Our code is developed in python 3.8 using Open3D, NumPy and SciPy libraries. The data is acquired using frontal the RGB camera and the ToF sensor (TrueDepth) of an iPad Pro 11" 2nd generation.

Go-ICP is executed in python, using a cythonized version of the original code of Yang et al. originally coded in C++. Calculations were done on a Linux Ubuntu computer with Intel® Core™ i5 -8365U CPU @ 1.60GHz 1.90 GHz, with 8Go of RAM.

Table 2: Matching results for the model of pipeline with our MCMH approach.

	Matching time (s)	Success rate (%)	RMSE (mm)	Fitness (%)
Scan 1	18.7 ± 1.1	90.5	0.83 ± 0.01	88.1 ± 0.8
Scan 2	16.5 ± 0.8	70	0.79 ± 0.03	87.4 ± 2.0

4.2 Systems Tested and Parameters

We performed our tests on two objects showed in Figure 3: a lego and a pipeline system. The lego object is approximately of 12 cm length, 7 cm width and 4 cm height. The pipeline object is 30 cm length, 10 cm width and 8 cm height. The last object represents well the inspection application since it is a reflective and complex object, made of steel. The lego is constraining by its size and sets the smallest object we successfully tested with our approach.

Table 3: Matching results for the pipeline and the lego models with Go-ICP. MSE Treshold is set to 0.00008. *Due to the computation time for this scan, only one calculation was performed.

Lego	Time (s)	Success	RMSE (mm)	Fitness (%)
Scan 1	18.7 ± 0.3	FALSE	0.99 ± 0.01	48.7 ± 2.0
Scan 2	19.9 ± 0.4	TRUE	0.63 ± 0.01	95.3 ± 0.9
Pipeline	**Time (s)**	**Success**	**RMSE (mm)**	**Fitness (%)**
Scan 1	20.8 ± 1.3	FALSE	0.994 ± 0.001	55.3 ± 0.6
Scan 2	3471*	FALSE	1.11*	23.1*

We now present the parameter used for the reconstruction and the global scan matching. We first begin with the MCMH parameters. Without any a priori, we must evaluate a large range of translations and rotations. So, we perform a large exploration in the first iterations. This allows us to move far enough from initial position. However, even if it helps to escape local minima, empirical tests show the need to restrain the range to access global minima. Metropolis-Hastings criteria is set to $\beta = 700$ (see equation (2)). MCMH procedure is computed over 10000 iterations. This allows enough sampling of the phase space to find the best approximate solution.

If luminosity can change during acquisition, we set the geometric parameter of ICP color $\lambda_{geom} = 1.0$. Voxel sizes from the coarse grain to the fine one are set to [0.01, 0.005, 0.002] for the lego model and [0.02, 0.01, 0.002] for the pipeline system. Adaptation of voxel size is needed for coarse to fine grain approach, depending on the size of the considered object.

We compare our method with Go-ICP. For this method, the matching calculations are performed on the complete point cloud of the scan and the model without a support plan. We choose to proceed like this since Go-ICP is combinatory and supposed to assure a perfect matching. The tests with Go-ICP are performed using the set of default parameters. Only the shutoff parameter, here a mean square error (MSE) threshold, is fixed empirically at 0.00008. Higher values tested did not gave satisfying results on all the tests. Lower values increase CPU time above the hour.

4.3 Scan Matching Performances

We first present the matching results we got for two different scans of the lego. These two scans are complex cases due to the low point density on the object point cloud. We evaluate four performance criteria: the computation time, the success rate, the RMSE and the fitness between the scan and the reference model. Since MCMH is stochastic, we evaluated 200 runs of our approach to quantify its robustness. RMSE and fitness are evaluated only for good results only. We define empirically that a good match corresponds to a fitness greater than 80%.

Results for the lego are presented in Table 1. We see our approach has an average success rate for the matching between 65 and 70% on 200 calculations. The time cost is about 13 seconds. We also saw empirically that RMSE and fitness can be used to evaluate the matching quality. A good matching has a value over 80% for the fitness and lower than the millimeter for the RMSE. The fitness is interesting since it traduces the overlap between the model and the scan, 100% means a perfect overlap.

We apply the same procedure to the pipeline model. Results are presented in Table 2. The computation time of the matching algorithm is 18 seconds. The success rate depends on the complexity of the scan. For example, the first scan tested show a rate success of 90.5% and the second, more complex, 70%.

For the Go-ICP method, since this approach is deterministic, one calculation is enough to get value for the four performances criteria previously described. However, stochasticity is added due to our scan preprocessing, so we evaluate the results on a set of 20 calculations. The Table 3 shows the results with this approach. Go-ICP is supposed to give the best matching without a priori, but for the two systems we tested, only one scan matching gives the expected results. The other tests were not retained since they converge to wrong solution. Due to its deterministic aspects, the only possibility to change results should be to change MSE threshold or initial orientation of the scans. However, modifying the MSE threshold does not improve results and requires more time to converge.

Our approach using MCMH shows interesting results. We have a ratio of success superior to 80% for most of the cases. However, difficult scan like scan 2 of the pipeline has a success rate of 70%, due to the quasi-symmetry of the object. Such phenomenon can be explained by the initialization before the matching. In term of phase space, the scan is positioned close to a saddle point. Due to this, in term of probability, we favor in the first iteration one side of the pipeline more than the other. In addition, the barrier between the two regions of the pipeline should be high. This implies that even with our metropolis criteria, passing the barrier is difficult. However, we treat a realistic industrial object, and we can assure correct matching if we keep only the best matching over the 200 tests. We already have leads to get performance improvement like taking the initial position and orientation of the scan into account thanks to IMU information. For the lego, we see it is a difficult case for matching. This is mainly due to the size and the point density of the scan. It implies less constrain compared to the pipeline and so, more local minima.

In term of computational time, our method is efficient. The complete matching algorithm took between 10 and 20 seconds for all the tested case. Our method is faster than Go-ICP. Half of the computational time is due to the point cloud pre-processing. For difficult cases, Go-ICP computational time can explode (~ 1 hour).

Finally, concerning the fitness and the RMSE, these two values are good performance criteria that can be used to interpret the matching quality. For most of the cases, a fitness value over 80% and with a RMSE below the millimeter means we have a good matching. In the case where Go-ICP shows good results, the method has a lower RMSE value and wider fitness value. Nevertheless, the adaptability showed by our approach is interesting for inspection application where objects are complex.

5 CONCLUSIONS

In this work, we proposed a MCMH approach combined with ICP for the point cloud matching problem. We showed encouraging results compared to a state-of-the-art method called Go-ICP. Our method includes a 3D reconstruction step using ICP color generating 3D models to compare scans. The method is efficient on small objects like the lego, and seems adapted to realistic objects for inspection problem like the pipeline system.

Our approach still suffers from some limitations, especially in difficult cases where there is some symmetry in the object of interest. The simplified triangular mesh descriptor we used could be too restrictive for such case, causing some trouble for matching. Some improvement can be done by changing the initial position of the scan for the matching. Parallelization of MCMH can also conserve efficient results while reducing the actual computation time of less than 20 seconds, which can let us consider a quasi-real-time application.

In the future, we plan to use this approach to perform geometrical comparison between a scan and its reference model, to highlight the presence of defects using similarity criterion. Highlighted region of interest will reveal the presence of defects like missing pieces, extra pieces or misoriented pieces. This method could then be used for detection of foreign objects in aeronautical assembly lines or missing pieces for maintenance for example. Further tests on realistic industrial environment, with different object sizes and complexity, are also planned to validate the method usability. A last improvement for this method could be to simulate a video processing approach through the fusion of several partial scans to inspect before comparing with the 3D model. It could improve robustness by adding more information and increasing artificially the sensor precision.

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