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# Predicting shim gaps in aircraft assembly with machine learning and sparse sensing

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ABSTRACT

A modern aircraft may require on the order of thousands of custom shims to fill gaps between structural components in the airframe that arise due to manufacturing tolerances adding up across large structures. These shims, whether liquid or solid, are necessary to eliminate gaps, maintain structural performance, and minimize pull-down forces required to bring the aircraft into engineering nominal configuration for peak aerodynamic efficiency. Currently, gap filling is a time-consuming process, involving either expensive by-hand inspection or computations on vast quantities of measurement data from increasingly sophisticated metrology equipment. In either case, this amounts to significant delays in production, with much of the time being spent in the critical path of the aircraft assembly.

In this work, we present an alternative strategy for predictive shimming, based on machine learning and sparse sensing to first learn gap distributions from historical data, and then design optimized sparse sensing strategies to streamline the collection and processing of data. This new approach is based on the assumption that patterns exist in shim distributions across aircraft, and that these patterns may be mined and used to reduce the burden of data collection and processing in future aircraft. Specifically, robust principal component analysis is used to extract low-dimensional patterns in the gap measurements while rejecting outliers. Next, optimized sparse sensors are obtained that are most informative about the dimensions of a new aircraft in these low-dimensional principal components. We demonstrate the success of the proposed approach, known within Boeing as PIXel Identification Despite Uncertainty in Sensor Technology (PIXI-DUST), on historical production data from 54 representative Boeing commercial aircraft. Our algorithm successfully predicts 99% of the shim gaps within the desired measurement tolerance using around 3% of the laser scan points that are typically required; all results are rigorously cross-validated.

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## 1. Introduction

Advanced manufacturing is increasingly becoming a data rich endeavor, with big data analytics addressing critical challenges in high-tolerance assembly [43], operation planning [33], quality control [42] and supply chains [27]. The broad applicability of data science in manufacturing is reviewed in [23,29,28,17]. Machine learning is a particularly promising tool for extracting actionable patterns in vast quantities of high-dimensional data that are difficult to visualize and/or interpret. Examples of machine learning in manufacturing systems abound, for example using topological data analysis [21], deep learning [47], and genetic algorithms to evaluate form tolerances [49]. Modern aircraft assembly is at the forefront of integrating big data into manufacturing, with advances in metrology accelerating aircraft manufacturing processes in recent years [46,25,44,45,39,43,36], for example in large composite structures [46], in fuselage skin panels [32], and in the wing box [12].

**Predictive shimming.** Aircraft are built to exceedingly high tolerances, with components sourced from around the globe. Even when parts are manufactured to specification, there may be significant gaps between structural components upon assembly. One of the most time-consuming and expensive efforts in part-to-part assembly is the shimming required to bring an aircraft into the engineering nominal shape. Historically, parts have

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been dry-fit, gaps measured manually, and custom shims manufactured and inserted, often involving disassembly and reassembly. Recent advancements in 3-D scanning have enabled their use for surface measurement prior to assembly, known as *predictive shimming* [25,46,44,12,45,43]. There are several patents and papers describing methods of high-tolerance measurement and manufacturing required for predictive shimming [37,38,12,4,52,51,5,1]. While some cost-effective devices may not provide the fidelity required, higher-fidelity metrology and scanning devices result in overwhelming amounts of data, shifting the burden from time-consuming manual shimming to time-consuming computational processing for predictive shimming. This amounts to significant delays in production, with much of the time being spent in the critical path of assembly. Reducing the burden of data collection and processing, and ultimately reducing delays for optimized aircraft assembly, could have significant financial implications.

**Sparse optimization in applications.** Digital measurement devices are inherently noisy. Statistical machine learning can be used to determine when – and *where* – higher fidelity is required. Additionally, part deformation can occur from measurement to assembly (due to external forces, climate, etc.). While not covered in this paper, machine learning can also be used to augment analysis to predict deformation. Several groups have used dimensionality reduction, such as principal component analysis (PCA) to model deformation in geometric surfaces for improved fitting [7,10,56,31]. In the automotive industry, PCA was used in combination with sparse sensing to identify key measurement locations for the characterization of compliant part assembly [7,10]. Such dimensionality reduction methods have also been compared with sparsity promoting techniques for outlier rejection and minimal description of surfaces [56]. However, this work is the first to combine RPCA with a scalable greedy sparse sensor optimization for robust predictive shimming in the aerospace industry.

**Contributions of this work.** In this work, we present an alternative approach to predictive shimming based on machine learning and sparse sensing. Instead of measuring each component of a new aircraft in isolation, we leverage historical production data to learn patterns in the shim gap distributions. In particular, the robust principal component analysis (RPCA) [8] provides an estimate of the dominant principal components that is robust to outlier measurements. Robust statistical methods are critically important for evaluating real-world data, as advocated by John W. Tukey in the earliest days of data science [24,13]. RPCA is based on the computationally efficient singular value decomposition (SVD) [20], and yields the most correlated spatial structures in the aircraft measurements, identifying areas of high variance across different aircraft. Next, based on the robust principal components obtained from historical data, we design a small subset of key spatial measurement locations that best inform the shim gap distribution of a new aircraft. Our procedure, known within Boeing as PIXel Identification Despite Uncertainty in Sensor Technology (PIXI-DUST), is based on recent advances in convex optimization for sensor placement [6,34,35]. We demonstrate the success of PIXI-DUST on historical production data from 54 Boeing aircraft, predicting 99% of the shim gaps within the desired measurement tolerance using approximately 3% of the available laser scan data. Specific contributions of this work include:

- Machine learning, dimensionality reduction and optimization are used to accelerate high-fidelity, measurement driven aircraft assembly.
- Our novel method extracts features and optimizes gap measurement locations to predict shim gaps in aircraft assembly.
- The proposed algorithm is demonstrated on historic Boeing aircraft production data.
- 99% of shim gaps are predicted within the desired measurement tolerance using 3% of the original laser scan points.

## 2. Mathematical preliminaries

The results in this work combine robust dimensionality reduction and sparse sensor optimization algorithms to dramatically reduce the number of measurements required to shim a modern aircraft. This section provides a foundation for the methods that will be synthesized and applied throughout the paper.

### 2.1. Robust principal component analysis

Least-squares regression is highly susceptible to outliers and corrupted data. Principal component analysis (PCA) suffers from the same weakness, making it *fragile* with respect to outliers. To address this sensitivity, Candès et al [8] introduced a robust principal components analysis (RPCA) that decomposes a data matrix $\mathbf{X}$ into a low-rank matrix $\mathbf{L}$ containing dominant coherent structures, and a sparse matrix $\mathbf{S}$ containing outliers and corrupt data:

$$\mathbf{X} = \mathbf{L} + \mathbf{S}. \tag{1}$$

The principal components of $\mathbf{L}$ are *robust* to the outliers and corrupt data in $\mathbf{S}$. The RPCA decomposition has tremendous applicability for many modern problems of interest, including video surveillance [3] (where the background objects appear in $\mathbf{L}$ and foreground objects appear in $\mathbf{S}$), natural language processing [26], matrix completion and face recognition [54].

Mathematically, the goal of RPCA is to find matrices $\mathbf{L}$ and $\mathbf{S}$ that satisfy

$$\min_{\mathbf{L},\mathbf{S}} \operatorname{rank}(\mathbf{L}) + \|\mathbf{S}\|_0 \text{ such that } \mathbf{L} + \mathbf{S} = \mathbf{X}. \tag{2}$$

However, neither the $\operatorname{rank}(\mathbf{L})$ nor the $\|\mathbf{S}\|_0$ terms are convex, and this is not a scalable optimization problem. Similar to compressed sensing [14,9], it is possible to solve for the optimal $\mathbf{L}$ and $\mathbf{S}$ with *high probability* using a convex relaxation of (2):

$$\min_{\mathbf{L},\mathbf{S}} \|\mathbf{L}\|_* + \lambda\|\mathbf{S}\|_1 \text{ such that } \mathbf{L} + \mathbf{S} = \mathbf{X}. \tag{3}$$

Here, $\|\cdot\|_*$ denotes the nuclear norm, given by the sum of singular values, which is a proxy for rank. The solution to (3) converges to the solution of (2) with high probability if $\lambda = 1/\sqrt{\max(n, m)}$, where $n$ and $m$ are the dimensions of $\mathbf{X}$, given that $\mathbf{L}$ is low-rank and $\mathbf{S}$ is sparse.

The problem in (2) is known as *principal component pursuit* (PCP), and may be solved using the augmented Lagrange multiplier (ALM) algorithm. The augmented Lagrangian may be constructed as:

$$\mathcal{L}(\mathbf{L}, \mathbf{S}, \mathbf{Y}) = \|\mathbf{L}\|_* + \lambda\|\mathbf{S}\|_1 + \langle \mathbf{Y}, \mathbf{X} - \mathbf{L} - \mathbf{S}\rangle + \frac{\mu}{2}\|\mathbf{X} - \mathbf{L} - \mathbf{S}\|_F^2. \tag{4}$$

A general solution would solve for the $\mathbf{L}_k$ and $\mathbf{S}_k$ that minimize $\mathcal{L}$, update the Lagrange multipliers $\mathbf{Y}_{k+1} = \mathbf{Y}_k + \mu(\mathbf{X} - \mathbf{L}_k - \mathbf{S}_k)$, and iterate until the solution converges. This is outlined in Algorithm 1. For this specific system, the alternating directions method (ADM) [30,55] provides a simple procedure to find $\mathbf{L}$ and $\mathbf{S}$. The parameter $\mu$ is discussed more in [55,8].

In the following, RPCA will be used to develop low-dimensional representations for high-dimensional aircraft metrology data (e.g., laser scans or point cloud measurements). In particular, the left singular vectors $\mathbf{\Phi}$ of the low-rank matrix $\mathbf{L}$ provide robust principal components, and are computed via the SVD:

$$\mathbf{L} = \mathbf{\Phi}\mathbf{D}\mathbf{V}^*. \tag{5}$$

These low-rank coherent patterns will then facilitate sparse sensing strategies.

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