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A Novel Sensing Template Using Data Fusion for Large Volume Assembly

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Abstract: The size of large components within manufacturing processes leads to complications with automating the processes required to assemble them into larger structures. In recent years, development of multi-sensor networks and breakthroughs in measuring algorithms have allowed for the creation of novel methods of mating large components. One major challenge with deploying sensor networks into production environments is the ability to attach sensors to large volume components. This can be remedied with the use of a sensing template that acts as a pseudo-virtual jig for the assembly process where sensors are embedded onto the template, thus not interfering with the physical assembly. The key step for this sensing template is creating an algorithmic process for accurate component localisation. This paper will introduce an innovative method of using data fusion attached to a sensing template embedded in an aerospace assembly process. A sensing algorithm utilising a Kalman filter allows for accurate component mating with a low error offset and high repeatability. The results of the sensing template show how it is capable of reducing the error offset and improves the repeatability of measurements.

Keywords: Autonomy, Manufacturing, Automation, Internet-of-Things, Sensing Enterprise

1. INTRODUCTION

The advent of the fourth industrial revolution has led to an influx of novel methods seeking to automate assembly processes. Lu (2017) notes that in the last several years there has been an increase in citations regarding *Industry 4.0* with innovative methods described by Hermann et al. (2016) increasing in popularity. One area of development is the localisation of components within assemblies, allowing autonomous or human operators to determine their accurate position. The surge towards Industry 4.0 has seen a considerable push towards developing sensing infrastructure that forms an intelligent machine with feedback to the overarching operation, mainly to avoid unaligned components leading to increased future maintenance costs (Resnick et al. (2018)). This sensing is the catalyst for data-driven actions within intelligent manufacturing using metrology-based adaptable sensing machines. An additional benefit of introducing sensing infrastructure into manufacturing is the ability to reduce errors that occur during the assembly process. Large-scale component assembly still poses as one of the most difficult section of production, due to the small tolerances and large components that are being used, as Jamshidi et al. (2010) notes for wing-box assembly mating to the larger aerostructure.

The motivation for this research is centered around the assembly of large components that require high accuracy placement. These components, such as the landing gear of an aircraft, cannot have sensors attached to them as there is the possibility of damage, nor can they be aligned using camera-based metrology due to the high accuracy requirements (Currey (1988)). Therefore, a method for allowing accurate mating of large-scale components needs to be developed that isn't using invasive sensor methods.

This paper will introduce a novel method for the assembly mating of two large components within manufacturing. This would give an operator or autonomous assembly method information to localise the component within the assembly structure and reduce the assembly offset error. Section 2 will discuss the literature surrounding sensor technology and large scale manufacturing. Section 3 will introduce the sensing template and the purpose of multi-sensor fusion from a manufacturing perspective. Section 4 will outline the experimentation procedure, detailing how the sensing template is being used to assist the process operator in the manufacturing task. Finally, section 5 will discuss the results of the experimentation on an industrial representative component assembly.

2. LITERATURE REVIEW

2.1 Dimensional Metrology in Manufacturing

Digital manufacturing provides an opportunity for production lines to gain insight into process information and feedback regarding the position, orientation and status of sub-components. To this end, *Large-Scale Dimensional*

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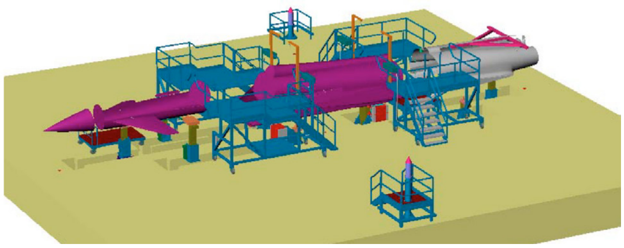

Fig. 1. Example of complete aerospace fuselage mating using an automated jig. Extracted from Rüscher and Mayländer (2001)

Metrology (LSDM) seeks to provide operators the same level of precision for the increased tolerances for manufacturers to achieve. Franceschini et al. (2014) explains how, as the demands of manufacturing regarding tolerances and increasingly small measurements increased, the need for more accurate measuring systems became more apparent. Franceschini et al. (2014) also note how hybrid and multi-sensor systems produce better results. Such novel sensing methods have seen prevalence in the automotive industry where sensor technology has been used for both manufacturing and post-production dimensional inspection of components as shown by Kiraci et al. (2020). LSDM systems comprise of large volume components, which in aerospace manufacturing can be wing boxes, sections of the fuselage or components inserted into aircraft sub-assemblies. Measuring these components accurately requires metrology systems capable of handling large structures with small tolerances. These systems can be separated into two distinct methods: non-contact and contact methods (Jamshidi et al. (2010)). Contact systems such as *Coordinate Measurement Machines*(CMMs) require either pre-programmed paths or external sensing tools to localise themselves. However, in a production line environment these tools can interfere with the components within the assembly. Jamshidi et al. (2010) states the use of such contact methods can prove to be a complex topology problem, leading to long development times and design periods for developing such *Collaborative Robots* (COBOTs) requiring safety measures when operating in human environments, described by Muijs and Snijders (2017).

One method to develop autonomous build processes for manufacturing is through specially designed jigs and fixtures suited to specific tasks or sections of the production line. The benefit of such methods are their high repeatability and reliability when performing manufacturing tasks. Such machines as those described by Mei and Zhu (2021) and Rüscher and Mayländer (2001) show how dedicated sections of the production line can be automated to a high degree of success by tailoring the process to the exact specifications of the sub-assembly in question. However, as Rüscher and Mayländer (2001) show in figure 1, their solution is only applicable to the specific method being performed. Additionally, attaching the sensors to the aircraft components can damage them prior to deployment, which within the context of aerospace manufacturing can be a costly process.

2.2 Sensing Innovation

Due to the increasing desire for more accurate methods of measuring distances in manufacturing, sensing innovation has become a priority within academic research. Sensor design has progressed to the point where sensor networks described by Franceschini et al. (2014) are more appropriate than single sensor systems, especially considering how the overall displacement error in an autonomous platform is based on the error propagation through the sub-systems in the process. Jayaweera et al. (2010) explains how the overall error is a factor of both the sensor and robot error. Sensor fusion can provide a robust distance measurement method by ensuring the movement of the autonomous machine - as well as the final error in the displacement - is governed by the smallest tolerance of the network. Furthermore, Jayaweera et al. (2010) shows that relying purely on a robotic arm for a pre-programmed path would still result in a propagation of uncertainty, with the result being a jig which is off it's desired position and has no method of determining it's pose. This reason alone drives the industry to develop sensing infrastructure to aid in both human and machine operated tasks.

One area of major development for sensing technology is the use of photogrammetry. Although cameras are not prevalent within manufacturing environments, the development of multi-sensor data fusion has allowed camera-based measurement to act as a separate measuring tool that assists the main sensors in their operation. Such systems are denoted by Luhmann (2010) as *on-line systems* that utilise process control and data acquisition in a feedback loop to allow for greater control of components. Methods described by Luhmann (2010) are industry-appropriate when used in partnership with classical sensor types. Recent novel methods for camera metrology have also led to the ability for measuring distances and generate dimensions and 3D models from single images such as that from Criminisi (2001). Criminisi notes that image and subject resolution influence the ability to accurately determine dimensions of objects in the field of view. Therefore, using camera metrology as the sole measurement tool in an automated system would be an unwise choice, where it should alternatively be used to complement other classical sensor types.

2.3 Multi-sensor Systems

Classical sensor methods all present some form of error or offset when used in isolation of one another. This can be in the form of randomly distributed noise spread across the data stream causing uncertainty in measurements. Such sensor noise can be the reason why many manufacturers abstain from using them in their production facilities, despite the ability to perform calibration during field operations as shown in Luhmann (2010). One approach is to combine multiple sensors each providing information regarding the pose of the component. This method has been defined as *multi-sensor fusion* and has seen prevalence in research when developing robust information systems for complex systems. Additionally, these sensor networks are subjected to the same statistical distribution, notably as a multivariate probability distribution:

$$f_X\{x_1, ..., x_k\} = \frac{\exp\left(-\frac{1}{2}(\mathbf{x}-\mu)^T\mathbf{\Sigma}^{-1}(\mathbf{x}-\mu)\right)}{\sqrt{(2\pi)^k|\mathbf{\Sigma}|}} \quad (1)$$

Where μ is the vector of means for the sensors and Σ is the covariance matrix. In equation 1, the joint probability density function (PDF) of k signals allow for the estimation and tracking of multiple sensors values in a single application. Ahmadi-Pour et al. (2017) shows the statistical models of the sensors on a self-driving car can be combined to provide a position estimate of the car and it's surroundings, allowing safe navigation through the environment with little operator input.

Multi-sensor fusion has seen extensive use for the design of fault resilient systems. Such systems rely on a level of tolerance for faults to become compliant for certain engineering applications, particularly when these systems operate in non-permissive environments. Nelson (1990) details how fault tolerant systems are used to avoid the possibility of systems being unable to report on their status when working in non-permissive dangerous environments. These N-modular systems can sustain failures to the sensors whilst still maintaining the capacity to deliver information to the operator. This is also commented on by Elmenreich (2002) where the *competitive fusion* of various sensors can be used to make systems resilient to failure. Sensors can also be aligned in *cooperative fusion* where sensors are used in collaboration to provide a complete view of an observed situation. For assembly procedures, cooperative fusion would allow for pose tracking of a component through the measurement of multiple sensors, as shown in figure 2. The systems that these configurations are deployed in can be shown to have temporal constraints, where there is hard and soft real-time constraints concerning actions undertaken by the systems. Unlike soft systems, hard real-time systems have temporal constraints which would lead to catastrophic failure if these constraints are not met. These systems have at least one hard deadline that must be met benefiting from a sensor network that allows for a redundancy and, combined with a cooperative fusion algorithm, would allow for more accurate and reliable system that is resilient to error propagation. In the next section, we will introduce an algorithm that combines multiple sensor inputs and utilises a cyber-physical architecture to combine the measurement and process domains.

3. SENSING TEMPLATE DESIGN

3.1 Sensor Network

Designing a sensor network for resilient cooperative fusion requires choosing different sensing technologies for certain distances. As noted in section 2.1, aerospace manufacturing is governed by tight tolerances, therefore the sensors used in the network would need to be capable of providing accurate measurements over a short distance to allow for accurate component placement. Sisinni et al. (2018) explains how the use of IIoT within Industrie 4.0 becomes a necessity when developing smart manufacturing tools, a statement echoed by Baumann et al. (2020) when discussing how smart sensors can be integrated for wireless control of smart devices in industry. In this application, the sensing network would require a sensor on each axis that is isn't physically constrained during the assembly process, so would require two sets of sensors on the $x-$ and $y-$directions. For the sensor network put forward in this paper, two circumstances need to be considered. The first is that the component is at a distance away from the final assembly position and the distance can only be measured with a ranged sensor. This paper will consider two different sensing types as possible technologies to use in the template: IR/photonic and laser sensors. IR sensors use an infrared beam and measure the distance to the surface through the intensity of the reflection from the surface, whereas laser sensors emit a pulse of light then measure the time taken for the laser to return after being reflected off the surface. To distinguish between the two sensors, we can compare the measurement resolution when subjected to ideal operating conditions. The resolution of laser *Light Detection And Ranging (LiDAR)* sensors can be determined from the minimum duration of the pulse emitted from the sensor. The relationship for the range can be determined from McManamon (2015):

$$\Delta R = \frac{ct}{2} \quad (2)$$

In equation 2, c is the speed of light in a vacuum, $3 \times 10^6 m/s$, and t is the duration of the pulse in seconds. From the data sheet for the sensor available at RSOnline (2020), we are told the shortest pulse duration is $1 \times 10^{-12}s$, yielding a resolution of $0.15mm$. For the IR sensor, the resolution of the sensor is determined by two factors: the resolution of the analog-to-digital converted (ADC) and the distance range available for the sensor Fraden (2016):

$$\delta = \frac{x_R}{2^M - 1} \quad (3)$$

Where M is the bit resolution of the ADC and x_R is the distance range of the sensor. Using the data sheet from Farnell (2020), we can calculate the theoretical resolution δ of the IR sensor to be $0.068mm$. From these two values, we can see that what the IR sensor loses in range to the laser sensor, it achieves far better resolution when measuring distances. Therefore, for close-range accurate measurements, an IR sensor would a more appropriate choice for our sensing network.

The second type of measurement needed in the sensor network is a close range measurement for precise component alignment. This level of precision cannot be afforded to range sensors due to the presence of noise and uncertainty in measurements (Fraden (2016)). Instead, the use of a limit switch can provide the template a high precision and repeatable measurement method when paired with the ranged distance sensor.

The final part of the sensing network is the photogrammetry system. As mentioned in section 2.2, photogrammetry as the sole sensing mechanism does not have the accuracy necessary for high tolerance manufacturing. However, as noted by Aldao et al. (2021), classical sensors can be used in parallel with photogrammetry. For this, using a camera as a secondary tool alongside the distance sensors and limit switch would allow for greater component manipulation in the cooperative fusion discussed by Elmenreich (2002).

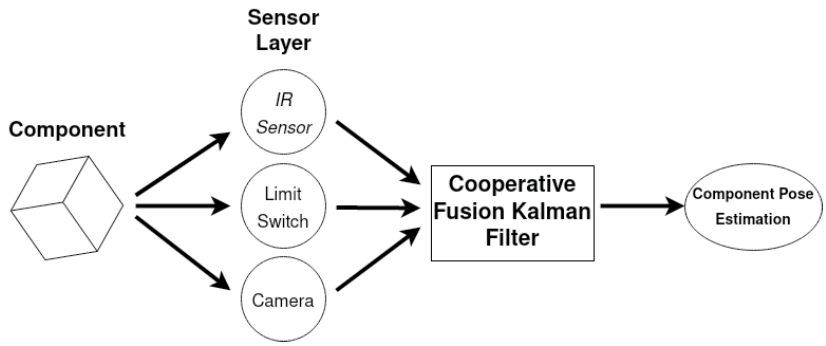

Fig. 2. Cooperative sensor fusion being used to generate a complete view of a component's pose. Adapted from Elmenreich (2002)

3.2 Sensing Filter

To maintain accurate tracking of distance measurements from the ranged sensor, the use of a filter is required for smooth operation. As mentioned in section 2.3, sensors suffer from uncertainty in their measurements due to the presence of Gaussian noise. To avoid this, a linear Kalman Filter (KF) algorithm is applied to the sensor readings for improved tracking as shown by Hussein (2008). The first step in the filter is prediction of the measurement for the current step. From Saho (2013), this is carried out as follows:

$$\tilde{\mathbf{x}}_k = \mathbf{\Phi}\hat{\mathbf{x}}_{k-1} \tag{4}$$

Where $\hat{\mathbf{x}}_{k-1}$ is the estimate of the previous time step, $\tilde{\mathbf{x}}_k$ is the prediction of the current time step and $\mathbf{\Phi}$ is the state transition matrix between $k-1$ and k. For a linear system, $\mathbf{\Phi} = 1$. The next step in the algorithm is the conversion from a prediction to an estimation:

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_{k-1} + \mathbf{K}_k(\mathbf{z}_k - \tilde{\mathbf{x}}_k) \tag{5}$$

In equation 5, $\mathbf{K}_k$ is the KF gain and $\mathbf{z}_k$ is the raw sensor measurement. This provides the estimate at the current time step $\hat{\mathbf{x}}_k$ based on the change in measurement value and the prediction based on the KF gain. The justification for using a Kalman filter over more modern tracking solutions proposed by Bar-Shalom et al. (2001) is to prove that the sensing template design and algorithm can be adapted to a variety of filtering techniques such as Bayesian and particle filters (Thrun (2005)) with relatively ease whilst still providing accurate results with an algorithm as simple as a Kalman filter. can now use this algorithm and the sensor network to build the sensing template and observe it's performance in an assembly process.

4. EXPERIMENTATION

4.1 Experimental Setup

The sensing template will be used for the alignment of a representative component within an assembly process required to be within $10mm \pm 0.5$ of the boundary face in the x- and y-directions. Two sensors are situated in each dimension: one micro-photonic IR sensor from Farnell (2020) and one limit switch from OMRON (2020). Additionally, the y-direction has a Raspberry Pi camera module that is used for alignment verification to test the efficacy of photogrammetry techniques for metrology processes. The sensors are connected to a Raspberry Pi 4 that is used for processing and deploying the algorithm to the sensors which output to the operator the position of the component within the assembly. The goal of the operator is to align the component within the assembly as accurately as possible using the sensing template as a guide. There are three scenarios being used for comparison and each scenario will be tested multiple times, followed by the plotting of the final position error distribution.

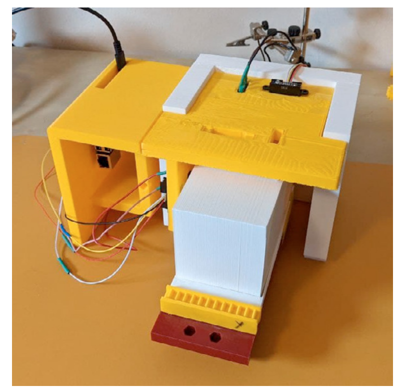

Fig. 3. Experimental setup using a Raspberry Pi 4 with the integrated sensing template

Scenario 1: The operator has no access to any sensor information and is using the current industry method of inserting the component, checking the alignment then re-inserting the component if the alignment is incorrect.

Scenario 2: The second scenario sees the inclusion of the IR ranged distance sensors that provide the filtered distance measurement to the operator for alignment assistance.

Scenario 3: The final scenario has the complete sensor network of ranged sensors and limit switches that provide the operator with precise position feedback.

4.2 Sensor Filtering Results

The first part of the algorithm to examine is the performance of the Kalman filter when estimating the distance measurement. To analyse it's performance, the filter will be compared against the raw sensor reading z_t at discrete

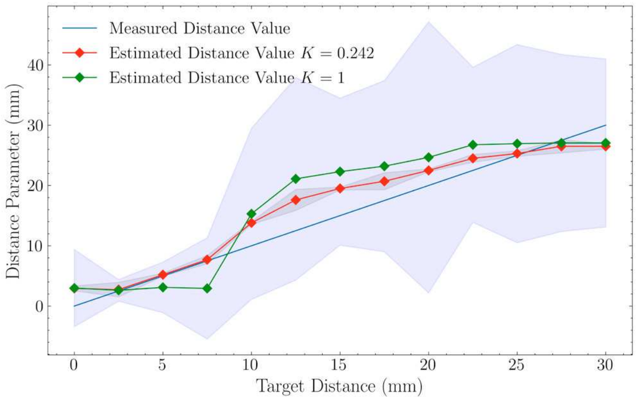

Fig. 5. Comparison of KF estimated value against sensor reading with the variance of each value shown in the shaded area

distance values from the sensor. The variation in the measurement value, σ_v, will also be plotted to evaluate the filter's ability to reduce the uncertainty in the measurement.

Figure 5 shows that the Kalman filter provides more accurate tracking of the actual value of the measurement compared to the raw measurement from the sensor. This tracking is controlled by the KF gain K_k, allowing for adequate tracking of signals with minimal tuning. With increased gain tuning, further improvements to the tracking capabilities could be achieved. Another benefit of the filter is the reduced uncertainty in the measurement, which has high appeal in manufacturing by providing operators with a higher degree of confidence in the system measurements.

To analyse the camera metrology performance, the camera will evaluate the alignment along an axle hole. This algorithm uses the Hough circle transform detector by Yuen et al. (1989) to calculate the offset in the y-direction from this image. Figure 6 shows the offset δ is determined from the two axle holes, one in the outer assembly and one in the component. Techniques such as this can be applied to manufacturing for precise component orientation, and the increase in computational power available manufacturers means these methods can be applied live during processes for immediate feedback.

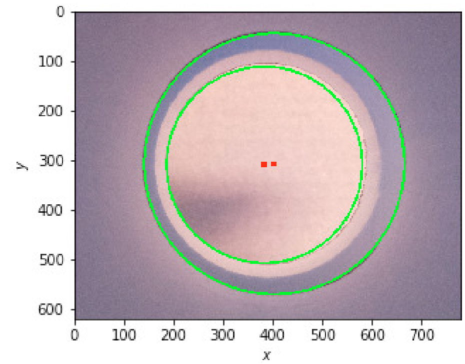

Fig. 6. Hough circle transform showing the difference δ between the axle holes

Table 1. Table of Mean μ and Standard Deviation σ. Values in mm

Scenario	μ_x	μ_y	σ_x	σ_y
1	1.225	0.50	3.144	2.185
2	0.325	2.10	1.381	1.991
3	0.025	0.85	0.680	0.709

4.3 Sensor Network Results

The final set of experimentation results concerns the performance of the sensing network in the three scenarios provided. Figure 4 shows the PDFs for the three scenarios and how the addition of the ranged distance sensor then the complete sensing network tends the mean error value towards zero in both the x- and y-directions.

Table 1 shows scenario 3 improves the average final offset value by 98%, with both mean values tending towards zero. The standard deviation in the error values reduces towards zero, indicating the sensing network produces more reliable tracking and repeatable measurements compared to aligning the components by eye. However, this standard deviation is still relatively high for manufacturing applications, namely due to the uncertainty in human movements (Smith and Reynolds (2016)). This could be remedied by using an autonomous platform that is capable of high precision and repeatable movements.

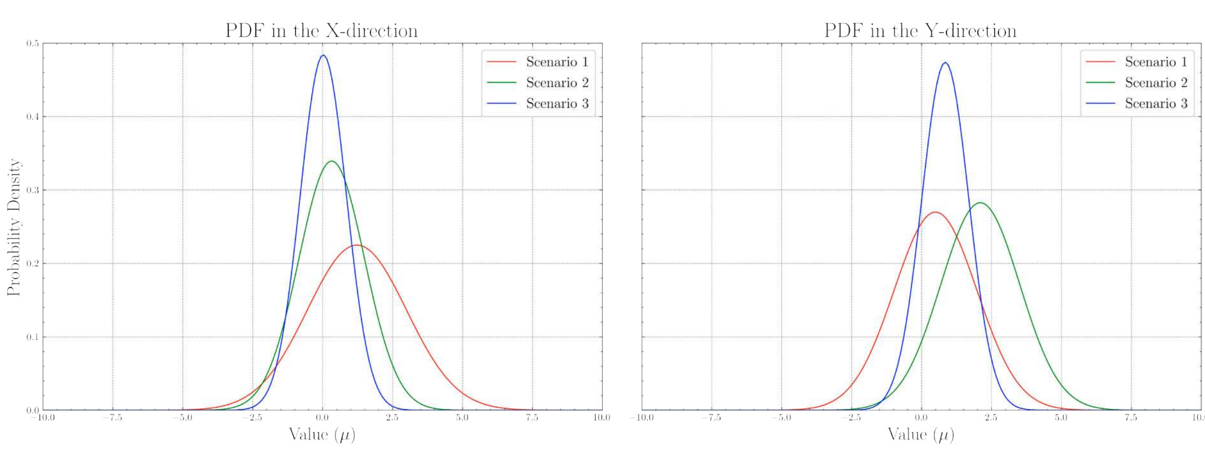

Fig. 4. Probability distribution for each scenario in the x- and y-direction

5. CONCLUSION

In this paper, we have shown how the use of a novel sensing template containing an embedded sensor network can reduce the offset and spread of data when mating large volume components within an assembly. We reviewed current metrology and autonomous assembly methods, and provided results which support our hypothesis of using multi-sensor data fusion for on-line manufacturing metrology. Further work would use the sensing template to aid autonomous assembly processes as described by Muijs and Snijders (2017) and to develop graph-based networks that provide more information regarding component pose as used by Mascaro et al. (2018).

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