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Detection of Deformations in Spiral Bevel Gear using Low-cost Depth Data Sensing Technology for Additive Manufacturing Remanufacturing Application

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ABSTRACT

Spiral bevel gears are important components in many mechanical systems. Their complex geometry, characterized by curved teeth following a spiral path, allows for smooth operation under high loads but presents significant challenges in inspection, and maintenance. Traditional methods for detecting gear deformations often rely on manual inspection, resulting in system downtime and high costs. This study focuses on detection of geometrical deviations in the three-dimensional geometry of spiral bevel gears. The need for high-resolution data capture and efficient large-scale data processing makes the problem more challenging. The objective of this work is to propose an algorithm using depth data from mobile phone-based depth sensing cameras to detect deformations in spiral bevel gears in a non-invasive way and compare the results of these algorithms with state-of-art methods. The methodology uses an iPhone 13 Pro's TrueDepth camera, capable of capturing depth maps at 640x360 resolution and a computational framework involving frame synchronization, NaN-handling, and differential analysis to construct a digital mold of ideal gear geometry. For deformation detection, an algorithm was created to compare individual depth frames against the created mold, utilizing threshold-based filtering and statistical analysis. The algorithm achieved perfect classification performance, correctly identifying all 94 non-deformed and 14 deformed gears without any errors. In conclusion, the deformation detection algorithm demonstrated high accuracy in identifying gear anomalies, with the confusion matrix confirming excellent classification performance between deformed and non-deformed frames. The findings of this paper contribute potential applications extending beyond gear systems to other critical mechanical components.

Keywords: Spiral bevel gear; TrueDepth camera system; computational framework; additive manufacturing; remanufacturing

INTRODUCTION

Gears are essential components in mechanical power transmission systems. Spiral bevel gears (Figure 1) are vital parts found in nearly all automotive differential gearboxes and main rotor drive systems of rotorcraft. Given the need for maximum power capacity, reduced weight, and high reliability, the fatigue strength of each gear is crucial. Spiral bevel gears play a vital role in automotive differential gearboxes by enabling smooth and efficient transmission of torque between non-parallel shafts, making them critical to vehicle performance, safety, and reliability (Xu et al. 2021; Liu et al. 2023). These gears are constantly under heavy load, high rotations and power swings (Wang et al. 2024). Hence, it is important to correctly operate the gears, otherwise the results will be catastrophic (Bo et al. 2020; Escudero et al. 2022). Failure of a gear during operation results in not only higher replacement or repair costs but also system downtime (Joshi et al. 2014). Therefore, early detection of gear failure is crucial to minimizing these expenses (Bhavi et al. 2021).

Gears can fail in many ways, however, for tooth interiors, fatigue fracture is the main failure mode (Erkka et al. 2024). Multi-stress state leads to changes in the geometry of the contact surfaces during wear cycles (Ignatijev et al. 2024). The spiral gears experience different types of deformation during their lifespan. Deformation that occurs in spiral bevel gears deformed under heat treatment is related to material composition, internal stress, and temperature change (Wang et al. 2023). This interaction inevitably induces tooth shape errors which influence the performance of meshing transmission and shorten the service life of gears (Ding et al. 2021; Khorasani et al. 2023).

Artificial Intelligence (AI) provides a solution that is superior to traditional methods in fault detection and diagnosis, including reduced human intervention, which relieves experts from tedious tasks (Yusoh et al. 2021). Nevertheless, these approaches still need significant learning and improvements to be effective and practical for more complex fault detection and diagnosis challenges in real-world scenarios (Tayyab et al. 2021; Habeeb et al. 2023). Despite the potential of AI, it remains underutilized in design optimization. However, AI is essential for processing the vast amounts of data required for optimization, including damage types, damage severity, material properties, and design constraints. These inputs are critical to achieving effective and adaptive repair strategies. To fully realize its potential, AI must be combined with big data analytics to enable an integrated, intelligent optimization framework within remanufacturing process (Habeeb et al. 2023).

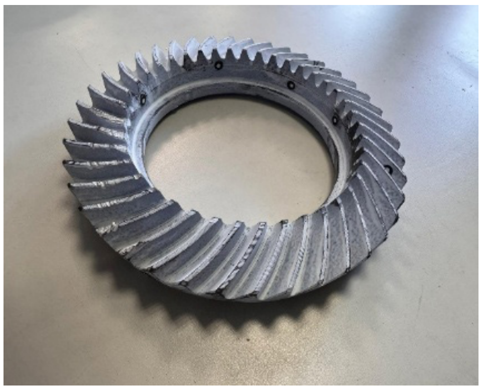

FIGURE 1. Spiral bevel gear

Advances in defect detection have benefited with the incorporation of process monitoring and machine learning in additive manufacturing (AM) (Habeeb et al. 2023). Additive manufacturing is capable of fabricating complex shapes layer-by-layer (Azman et al 2021) for the automotive industry (Othman et al. 2024). Recent studies and the use of machine learning improve defect detection in AM. Advanced monitoring techniques make it possible that potential defects can be identified and corrected quickly, yielding high-quality results (Herzog et al. 2024). Object detection creates a model or technique that will help in computer vision applications to obtain a part's geometrical data (Alhardi & Afeef 2024).

In manufacturing and maintenance, non-invasive detection technology advancements are important towards smarter, sensor-driven techniques. These technologies allow the detection of defects and anomalies in advance without disassembly or impact to operational elements. Hence its importance in protecting machinery integrity and prolonging their lifecycles. Non-invasive inspection techniques in industrial maintenance are crucial, which can save money, lives and production time (Alotaibi et al. 2021). Non-invasive technologies include an array of imaging modalities beyond depth sensors, for example infrared thermography, ultrasonic imaging and optical coherence tomography. However, the best technology is dependent on its application.

Infrared thermography quickly spots thermal anomalies that signal high friction or wear, while ultrasonic imaging unveils sub-surface flaws that no other techniques are be able to detect. These methods are useful for the qualitative assessment that can be performed without affecting the material quality of the component (Avateffazeli & Haghshenas 2022). Non-invasive detection technologies are widely used in industries like Aerospace and Automotive market sectors where component reliability is necessary for safety. Laser scanners are often used in the aerospace industries to evaluate the conditions of turbine blades. In automotive manufacturing, ultrasonic sensors are used to ensure the welds meet quality standards during assembly. These examples demonstrate the critical role of leading-edge imaging and sensing in today's manufacturing to increase product reliability and safety (Yang et al. 2020). Additive manufacturing has an important role in remanufacturing (Yusoh et al. 2020).

Vision Based Inspection Systems such as TrueDepth cameras and structured light scanning based inspection methods are the future and lead the way ahead for new non-invasive technologies. The technology captures exact three-dimensional surface images, which allows the systems to detect any anomalies and dimensional faults. Components such as spiral bevel gears needing thorough inspection is important, where even minor deviations can cause operational failures. This makes the data collection high-resolution, allowing detailed surface topography analysis to be completed which is an absolute necessity for characterizing surface finish quality to the standards that are highly strict in precision engineering (Liu et al. 2023). The availability of Non-invasive detection technologies for maintenance, quality control and safety within manufacturing is critical. With the combination of state-of-the-art imaging technologies and powerful analytical tools, these methods are instrumental in maintaining product reliability as well as safety and enhancing operational efficiency in different industries.

Real-time detection of deformation and defects in mechanical components (i.e., spiral bevel gears) is an important task for repair and maintenance strategies. When repair is performed without accurate identification, the determination of the root cause may be missed and lead to suboptimal performance or further damage (Cao et al. 2020). Based on Tang et al. (2023), the application of machine vision quality assurance into surface defect detection in steel products facilitates a detailed examination of reworked gears to ensure that the surface integrity is maintained within rigid industry-specified limits.

Traditionally, manual inspection or costly equipment is the only way to detect gear deformation, so as a result, it causes long stoppage time and increase costs (Rahito et al. 2018). Nevertheless, deploying cutting-edge technologies such as depth sensing and additive manufacturing in gear inspection and repair processes can overcome this problem, leading to a reduction in downtime due to maintenance procedures, longer-lasting gears, and overall system reliability (Den Hollander et al. 2017). The latest developments in low-cost sensing technologies have led to revolutions of complex inspection procedures within industrial applications to control product quality. For example, (Haenel et al. 2022) report a successful application of the iPhone TrueDepth camera that provides reasonably high-resolution depth data at relatively low cost compared to other current devices and technologies used. The TrueDepth camera of the iPhone provides an economic method for high-resolution depth data acquisition (Haenel et al. 2022). It is an example of a technology which was developed for a consumer market but has been found to have other uses in the industry because of its precision and low cost. Low-cost sensors make this easy given its wide acceptance amongst the users and also can easily be incorporated with existing systems which encourages frequent monitoring and inspection without causing a huge concern in cost factor.

Computational methodologies, such as machine learning algorithms can process large datasets generated by imaging sensors to identify subtle patterns that human inspectors might miss. It should be noted that predictive analysis is one of the most crucial functionalities in predicting events within preemptive maintenance strategies, helping to decrease unforeseen downtimes and increase the longevity of machinery operation by detecting intricate trends that might slip past human inspectors (Grasso et al. 2021). However, While TrueDepth cameras in iPhones have high 3D data resolution, the TrueDepth camera is a structured light sensor system integrated into recent iPhone models, capable of capturing high-resolution depth data using infrared projection and stereo vision. There are no robust algorithms to detect the deformations of complex geometries like spiral bevel gears. Hence, creating the need for bespoke algorithms designed to analyses complex geometrical profiles. Previous research showed that high-precision inspection can be accomplished using consumer-grade depth sensing technology, potentially lowering the cost and increasing accessibility of advanced inspection techniques.

In practice, approach to gear geometric anomaly detection provides a powerful tool for non-invasive inspection of complex gear topologies. The aim of this paper is to develop a low-cost high accuracy method for the detection of deformations and defects in spiral bevel gears. The advantage of this method would be low-cost, leveraging depth sensing technologies (TrueDepth camera in iPhone) to measure precise deformations. The research aims to enhance the reliability and efficiency of gear detection processes, contributing to improved performance and longevity of mechanical systems. In this proposed method, an algorithm is also developed to obtain and analyse complex geometrical profiles of a spur gear.

METHODOLOGY

In this section, the proposed method to develop the low-cost high-accuracy detection of deformation and defects through depth data analysis and refinement in spiral bevel gears is presented. The Detection and Depth Data Acquisition Phase is important in detecting deformations in spiral bevel gears. This step takes advantage of low-cost depth sensing technologies for high-resolution data acquisition, essential for accurate deformation detection. As a result, the proposed method solves not only the issue of detecting deformations in situ but is also an important development in the context of mechanical diagnostics and condition monitoring.

In the following sub-section, the hardware and software requirements for this method are presented.

HARDWARE AND SOFTWARE REQUIREMENTS

The hardware and software specifications and requirements to apply this method is important to ensure that the method can be accurately applied. The development of a depth-based sensing system utilizing the iPhone's TrueDepth camera involves specific hardware and software pre-requisites to efficiently capture and process depth data for applications like geometric detection of tooth damage in spiral bevel gears. It is important for the successful implementation and operation of such a system.

In terms of hardware, an iPhone equipped with a TrueDepth camera is required. This feature is available in iPhone X and later models, which includes a sophisticated array of sensors capable of capturing detailed depth information. The TrueDepth camera system of the iPhone 13 Pro features a structured light infrared sensor capable of capturing depth maps at 640×360 resolution, with each pixel representing a 32-bit IEEE 754 floating-point depth value. The system includes a dot projector, infrared camera, and flood illuminator, providing sub-millimeter depth accuracy suitable for detailed geometric analysis of gear tooth profiles.

A single capture session can generate hundreds of megabytes of data, as observed with a 14-second capture resulting in approximately 380MB of uncompressed data. Compressing these files can significantly reduce their size, for example, to around 56 MB when zipped, but ample storage is necessary for processing and analysis of the images. Regarding computational processing power, the latest iPhone models with advance processors are preferred to handle the computational demands of real-time data processing, analysis, and machine learning tasks associated with depth data interpretation.

Figure 2 displays the frontal layout of a smartphone's depth sensing system, which is important for facial recognition and augmented reality applications. The system is composed of several key components (Liu et al. 2022), as presented in Table 1. These elements work together to provide a full depth-sensing package for tasks such as securing facial authentication, real-time 3D scanning and augmented reality (Liu et al. 2022).

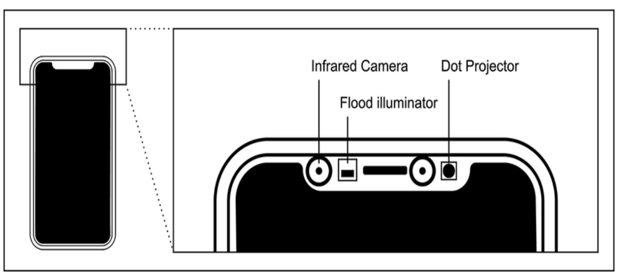

FIGURE 2. Frontal layout of a smartphone's depth sensing system.

TABLE 1. Hardware components and their functions

Component	Functions
Infrared Camera	Collects infrared images that are part of the input data for use in 3D perception algorithms under different lighting conditions.
Dot Projector	Projects a grid of invisible infrared dots onto the scene or object in front of the camera. These dots are displaced on surfaces in a pattern, which the system uses to calculate the distance and location of each specific point in 3D space.
Flood Illuminator	A dedicated light delivers more powerful depth-sensing capabilities, which is necessary for the enhancement of facial recognition.

Regarding the software in this proposed method, to obtain the results in form of depth data output from iPhone's TrueDepth sensor, it is required to record and capture the custom iOS application. This mobile application will need to be able to communicate with the camera hardware as a source of in-depth information and record this without any compression or data reduction to ensure that the accuracy and reliability of the captured data is not lost. For processing and analyzing the captured depth data, Data Processing Libraries such as NumPy for data manipulation and Matplotlib for visualization are indispensable. These libraries are designed to facilitate handling big-data and to support the creation of depth algorithms. This method uses Xcode and Swift as iOS development environment for mobile application developers. A good understanding of frameworks that support augmented reality applications is also required, such as ARKit and how it can improve the depth sensing.

PROPOSED METHOD FOR LOW-COST HIGH-ACCURACY DETECTION OF DEFORMATIONS AND DEFECTS

The proposed methodology relies on consumer-grade hardware and open-source software, which significantly reduces implementation costs compared to traditional industrial 3D scanning systems. The iPhone 13 Pro with the TrueDepth camera, offers a high-resolution depth sensing capability at a fraction of the cost of industrial laser scanners or structured-light 3D imaging systems. The use of low-cost consumer hardware (iPhone 13 Pro) instead of high-end 3D scanners which costs 10-20 times more, microwave turntable, and open-source data analysis libraries (NumPy, Matplotlib, SciPy) provide a highly cost-efficient alternative to traditional industrial gear inspection setups. As shown in Figure 3, in the flowchart, each step is presented and described in this section. In the proposed method, the TrueDepth camera is a crucial technology in the setup that can capture high-quality depth data using Capture File Type class. A digital “Mold” or twin of the ideal gear geometry is then constructed, serving as a reference for comparison with the actual part. Critical steps such as frame synchronization, handling Not a Number (NaN) values, differential analysis, and threshold-based filtering are meticulously discussed in the proposed method.

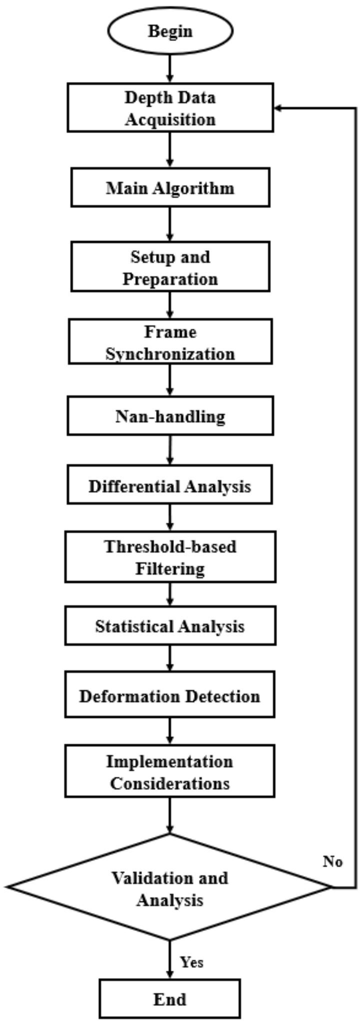

FIGURE 3. Method for gear deformation detection through Depth Data analysis and performance refinement

The acquisition of depth data using TrueDepth camera in iPhone through a custom iOS application consists of several steps, each step is important in the process of capturing and handling high-quality depth information. These steps demonstrate the relationship between hardware functionalities and software algorithms to develop gear deformation detection through depth data analysis. To set up the rotation of the spur gear, a rotating platform is coupled with the angular positioned spiral bevel gear so that each face would be precisely detected. The spiral bevel gear is placed on a rotating plate of a microwave turn plate. This method takes advantage of the rotation feature as a turntable to continuously and smoothly turn the gear so that TrueDepth camera can systematically record all dimensions and details of the gear surface and avoid involvement of manual actions. The TrueDepth camera found in the iPhone 13 Pro captures depth information while spinning the gear in multiple directions.

The TrueDepth camera consists of an infrared camera, dot projector and flood illuminator project a pattern of invisible infrared dots on the gear as it rotates. The camera charts out the dots and the deformation upon touching the surface of the gear. This detailed map of depth of the gear is drawn against each angle as it rotates through. The iPhone stands still with the camera focused on the equipment to guarantee that depths are captured from the same perspective which is essential for correct 3D models and analysis during post-processing. This data is later saved in binary version, then processed and analyzed. The iPhone 13 Pro’s advanced capabilities are used to deliver depth data with the highest possible level of precision so that deformations can be detected and analyzed accurately. Some processing is applied to the depth data after it is captured, as it is stored in its raw state, so that any analysis conducted using this data can serve up the most accurate signals possible. The frames are ordered and stored in binary files, padded with zeros to memory or cache for efficient data passing. The storage format was designed to handle large amounts of data captured in each recording, consisting of short recordings with extremely large file sizes.

Upon storage, frames are examined on a per frame basis to determine the quality of depth measurement and to identify failure cases. Essentially, where the depth measurement fails (typically at the edge of the image or beyond the sensor range), these frames contain on NaN values for the pixels. It is important to highlight these limitations to help refine the depth sensing process and the accuracy of any measurements made.

Color gradients are used to visualize depth changes across frames using heatmaps to make the data more interpretable. This is useful for separating areas of interest (like industrial gear teeth during inspection), by only looking at a range of depth and setting the colourmap to be within that interval. Molds are an additional way to filter data, excluding irrelevant regions of the map into account-analysis areas.

In the final step, the individual paths or profiles are extracted in these sampled frames to analyze depth changes along these trajectories. Paths are drawn in a photograph to which techniques like ellipse fitting are applied to obtain the paths along depth can be analyzed. This approach is important in visualizing and quantifying the depth characteristics of intricate features, such as the gear teeth, providing insights into their conditions and structural integrity. Each step in the depth data acquisition process plays a vital role in harnessing the TrueDepth camera's capabilities for advanced applications.

ALGORITHM FOR GEAR DEFORMATION DETECTION

The algorithm created for gear deformation detection using the TrueDepth Camera and depth data is presented. The method developed is demonstrated to be both efficient and accurate and is a general-purpose refraction algorithm taking advantage of depth information provided by advanced imaging technologies like the TrueDepth camera system. The operation of the algorithm is mainly divided into three processes: Data Preparation and Pre-processing, Mold Creation and Deformation Detection.

DATA PREPARATION AND PRE-PROCESSING

Data preparation and Pre-processing are the first step, where binary files of depth data frames are processed. This is an important step to create a clean and synchronous dataset, aligned in terms of time or rotation phase between the depth data for each frame on a unique data series. This also includes managing NaN values which are a representation of unsuccessful depth measuring areas so that the data integrity stays intact during subsequent analysis.

After the data preparation step, an algorithm builds a "Mold". The Mold is a computational model that describes how the gear teeth would ideally look if they were deformed. This Mold is generated from depth based on many attempts of ordered collection, so it reduces noise and fills the gaps in data. Through the generation of a standardized gear-like Mold, this is an innovative method to be used for benchmarking the real conditions of gears.

The final step is the Deformation Detection. Once the model shows changes of deformation it helps the algorithm to check individual depth Data Frames against the Mold for deviations, this isn't just a simple subtraction: instead, it requires complex differencing and thresholding to distinguish between normal wear and tear from large-scale deformation, that warrants attention. The main algorithm of Gear Deformation Detection is shown in Figure 4.

```
Input:
   captures: List of Binary files containing depth data frames
   gearGeometry: Parameters defining the gear's expected geometry
Output:
   deformationReports: List of Reports detailing detected deformations
Procedure: MAIN ALGORITHM
   frames ← PREPAREDATA (capture)
   mold ← CREATEMOLD (frames)
   deformationReports ← DETECTDEFORMATION (frames, mold)
   return deformationReports
End Procedure
```

FIGURE 4. Main Algorithm of the Gear deformation Detection

Algorithm 1, which is the Data Preparation and Pre-processing (as shown in Figure 5) serves as a foundational step in the algorithm for detecting gear deformation, focusing on the meticulous processing of depth data captured in binary file formats. Initiated with a list of such binary files as its input, this procedure systematically transforms raw depth data into a structured and analysis-ready dataset, ensuring both the integrity and the consistency necessary for subsequent stages of the algorithm. For each file in the input list, a Capture File object is instantiated to facilitate efficient data handling, following which all frames within the file are extracted using the read All Frames method. These frames are then passed through the synchronized Frames function, aligning them in either temporal or rotational sequence to achieve uniformity across observations. The critical step of handling NaN values is executed via the handle NaNs function, addressing gaps or inaccuracies in the depth measurements to preserve data quality. Finally, the cleaned and synchronized frames are aggregated into the processed Frames list, culminating in a dataset optimized for the rigorous analysis that characterizes the Mold creation and deformation detection processes.

```
Input:
   captureFiles: List of binaries containing depth frames
Output:
   Frames: List of processed and synchronized depth data frames
Procedure: MAIN ALGORITHM
   Initialize an empty list: processedFrames
   for each file in captureFiles do
      capture ← new CaptureFile (file)
      rawFrames ← capture. readAllFrames ()
      syncFrames ← sychronizeFrames (rawFrames)
      cleanFrames ← handle NaNs(syncFrames)
      Add cleanFrames to processedFrames
   end for
   return processedFrames
End Procedure
```

FIGURE 5. Algorithm 1: Prepare Data Procedure

The Capture File class efficiently manages depth data streams across an entire volume without attempting to load the whole thing into memory. It makes performance gain quite significant because it is an efficient approach for loading data, where it reads the data only when it is requested, thus saves memory and keeps calculations effective.

The parameters for the class constructor are few, including the path of the file, frame size and an optional frame stored size which is defined to adapt other data formats and storage conventions. This permits the random access of an individual frame or batch and is capable of efficient data processing and analysis. Use cases where near instant feedback and or selective data inspection is a valuable feature.

MOLD CREATION

One of the essential stages that allows detecting subsequent teeth deformation is creating a “Mold” of teeth. This process creates a representative model (Mold) of the teeth obtained from the pre-acquired depth stream to which incoming frames can be compared for detection of deformation anomalies.

Frame synchronization is critical for the entire process of gear deformation detection with depth data, and this is a sophisticated step, required to temporary or rotational align the captured frames together, so that each frame corresponds to exactly one capture moment in time. This alignment is critical for a valid comparison between individual frames and the generated Mold, which acts as a benchmark for locating gear tooth anomalies. The objective of frame synchronization is to align on each gear’s rotational cycle so that the data clearly reflects a consistent point in that cycle across all frames, allowing for accurate anomaly detection.

The frame synchronization in Algorithm 2 (Figure 6) means ordering a sequence of depth data frames according to the rotational operation of gear. The reason for this is that the teeth of the gear, which are the main point to observe for deformation detection, move in and out from the camera’s field of view with its rotation. Since the movement is not synchronized, comparing between frames or to a reference Mold could lead to misleading results as they may show different gear positions.

A new characteristic of certain methods for frame synchronization is the computation of a template frame by a recursive average over the chosen frames. This averaged result across a selection of frames where they are assumed to be time-synchronized forms the basis for creating an assembled image or Mold that string together depth data and represent what the gear surface usually looks like. In this context, the recursive mean is very well suited for its incremental addition of more and more data, decaying significance of typical outliers, and noise-purgingness.

After the synchronization, corresponding frames are averaged together to create a composite depth profile of the gear teeth. By averaging between each particle, this reduces noise and fills in missing data resulting in a reliable and high-resolution Mold. While converting features to Mold, data loss and NaN values are kept in mind (For ex- Average with condition and Data interpolation etc is used) The resulting Mold provides a “baseline” for evaluating structural regularity of the gear, encompassing the lost tooth profile due to distortion.

```
Input:
  Frames: Array of depth data frames for the gear
  NumTeeth: Number of teeth on the gear
Output:
  SycedFrames: Array of synchronized frames
Procedure: SYNCHRONIZED FRAMES (Frames, NumTeeth)
  PeriodRange ← DetectPeriod (Frames, NumTeeth)
  Initialize an empty list: SycedFrames
  for each period in PeriodRange do
    startIndex ← FindStartIndex (Frames, NumTeeth)
    endIndex ← startIndex + preriod * NumTeeth
    while startIndex , length (Frames) and endIndex ≤ length (Frames) do
      frameSubset ← Frames [startIndex: endIndex]
      referenceFrames ← CalculateReferenceFrames (frameSubset)
      SyncedFrames. append (referenceFrames)
      startIndex ← endIndex
      endIndex ← startIndex + preriod * NumTeeth
    end while
  end for
End Procedure
function DETECTPERIOD (Frames, NumTeeth) ◊ Period detection using the Manhattan distance
  return [basePeriod − 0.2 * basePeriod, basePeriod + 0.2 * basePeriod]
End function
function FINDSTARTINDEX (Frames, period) ◊ Identify the starting index for synchronization
  return calculatedStartIndex
End function
function CalculateReferenceFrame (frameSubset) ◊ Calculate the recursive mean of frameSubset
        to create a reference frame
  return referenceframe
End function
```

FIGURE 6. Algorithm 2: Frame synchronization

One of the most important processes when it comes to establishing this reference model, also called a “Mold,” is the ‘Calculate Recursive Mean Mold’. The process builds a Mold by taking an average of “key” frames obtained at different times, snapshots of the gear’s depth profile. Rather than a simple average, this uses a recursive mean algorithm which allows for an online and memory efficient way to compute the average depth of many frames.

For every pixel in the frame that has no depth measurement here the algorithm updates are incremented based on this new data point being integrated into the model. The recursive average involves performing the steps of algorithm 3

Hereby the current mean is modified with a multiplier representing proportional of difference between the new pixel value and the old Mean times data total processed points. Every time a new frame is added, the sum of all the frames before it will in turn have a more subtle influence on its shape, resulting in automatically continuing to fine tune and match each individual mold closer and closer towards overall average gear teeth geometry represented in all selected frames.

```
Input
  SelectedFrames: Array of selected frames within the period range
Output
  Mold: Reference frame representing the mold of selected frames
Procedure CALCULATERECURSIVEMEANMOLD (SelectedFrames)
  Initialize Mold with the first frame from SelectedFrames
  Initialize n ← 1 ⋄ n is the count of frames considered
  for each frame in SelectedFrames starting from the second frame do
    for each pixel in frame do
      if pixel value is not NaN, then
        n ← n + 1
        oldMean ← Mold[pixel]
        newValue ← frame[pixel]
        Mold[pixel] ← oldMean + (newValue−oldMean)/n
      end if
    end for
  end for
  return Mold
End Procedure
```

FIGURE 7. Algorithm 3 Reference Repeated Pattern (Mold) Creation using Recursive

Using the recursive mean which adapts every time a pair of observations is seen incorporates learning over time in the Mold, making it an effective baseline for anomaly detection. Finally, this synthesized depth profile of the gear provides an effective means to identify deflections due to wear or damage in the gear at high levels of accuracy and efficiency in Algorithm 3 shown by Calculate Recursive-Mean-Mold Process, as shown in Figure 7.

DEFORMATION DETECTION

The Deformation Detection Step Distorts the Analytic Data collected from Above to Reveal Deviations in the Gear Geometry compared with Mold. Deformation detection is made possible by comparing the Mold to individual depth frames. The comparison is based on the calculation of absolute differences whose values are examined for discrepancies that could indicate changes in shape. This procedure is complex and involves applying threshold-based filtering to differentiate normal variations from critical abnormalities. Certainly, this distinguishing is vital for identifying real deformable events as opposed to false positives that are mistakenly identified as deformations, and it guarantees the effectiveness of the detection.

Quantification of this deformation is accomplished by deriving deformation metrics which quantify how far, and to what degree a detected deviation from the status quo has occurred. These metrics are informed by the magnitude of the discrepancies between the Mold and the depth frames, offering a quantitative basis for assessing the gear's condition. These metrics are implemented using sophisticated data processing techniques that take advantage of concepts such as error thresholding and statistical analysis to ensure the detection and quantification of deformation phenomena.

Classification metrics are used to evaluate the accuracy and effectiveness of the deformation detection algorithms. These metrics help in determining how well the algorithms can identify and classify deformations in the gears, for example, accuracy, precision, recall (sensitivity), F1 score, and specificity. Accuracy is defined as the ratio of correctly identified deformations to the total number of instances evaluated. Equation (1) shows the formula for accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Where:
TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives

Equation (2) shows the precision, which is defined as

the ratio of true positive detections to the sum of true positive and false positive detections.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

Recall (Sensitivity) is the ratio of true positive detections to the sum of true positive and false negative detections, as presented in Equation (3):

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

The F1 Score, which is he harmonic mean of precision and recall, providing a balance between the two metrics, is presented in Equation (4).

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

The specificity, which describes the ratio of true negatives detections to the sum of true negatives and false positives detections, is shown in Equation (5).

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{5}$$

VALIDATION AND ANALYSIS

Implementing this algorithm within a computational framework requires careful attention to various factors, including computational efficiency, data integrity, and algorithmic accuracy. Efficient memory management, facilitated by the Capture File class, ensures that the algorithm remains scalable and responsive. The accuracy of the Mold creation and synchronization processes is paramount, as these steps lay the foundation for the subsequent analysis. Robust error handling and data interpolation strategies enhance the resilience of the algorithm, ensuring its applicability across a wide range of scenarios and data quality conditions.

Validation of the Deformation Detection Algorithm requires a thorough series of testing and studying, which includes both qualitative and quantitative analysis. Qualitative analysis, based on Visual Methods, is discussed and presented in the results section primarily through visual inspection techniques like heatmaps, depth profiles, and 3D visualizations. These show the detection of anomalies through visual color-coded representations. In this paper, quantitative analysis is also represented in statistical methods, representing the accuracy, precision, recall, F1 score, specificity metrics, and confusion matrix results. Visual analysis to individual frames helps intuitively understand the algorithm, statistical examination of the deformation metrics supplies a more quantitative point of view. Robustness evaluation requires experiments on different datasets which have various levels of noise and deformation to optimal parameter tuning for the algorithm to be investigated.

RESULTS AND DISCUSSIONS

A case study of a damaged spur bevel gear was conducted based on the proposed methodology. This section is structured to provide a detailed overview of the results from the deformation detection processes. Figure 8 shows an image that displays a spiral bevel gear with noticeable deformations on its teeth.

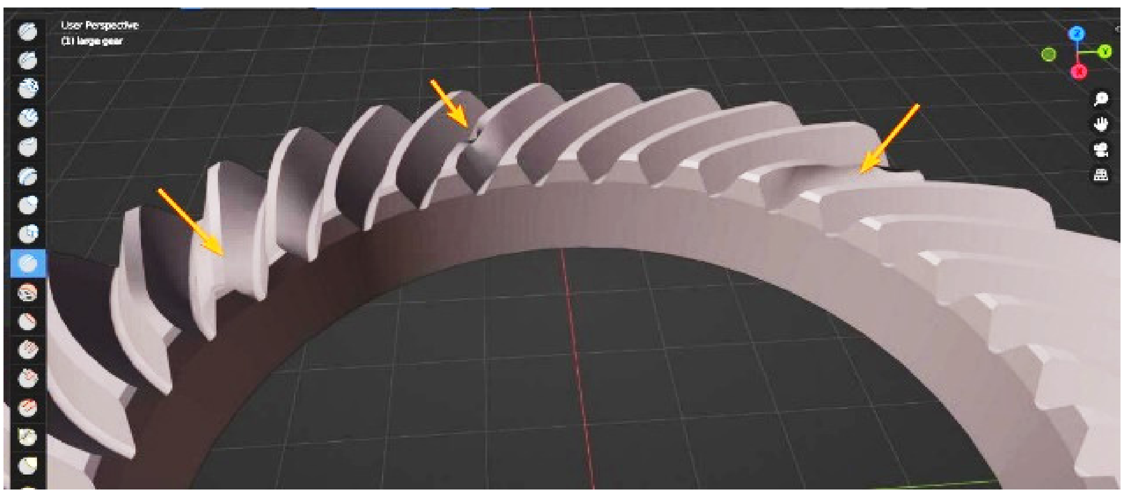

FIGURE 8. Image of a spiral bevel gear showing deformations on the teeth

INSPECTION RESULTS

In order to illustrate the process and effectiveness of depth data capture for a spiral bevel gear using advanced imaging technology, Figure 9 displays a sequence of frames captured using the iPhone 13 Pro's TrueDepth sensor. Each frame, numbered from #000 to #023, represents a snapshot in the depth data capture process. Initially, the frames exhibit minimal data, with substantial areas appearing black, indicating NaN values or the absence of captured depth information. As the sequence progresses, more depth information becomes visible, with frames around #012 to #015 displaying significant activity where the gear teeth become distinguishable. This progression demonstrates the sensor's capability to capture complex geometries over time, though the initial frames may necessitate pre-processing to address missing data effectively.

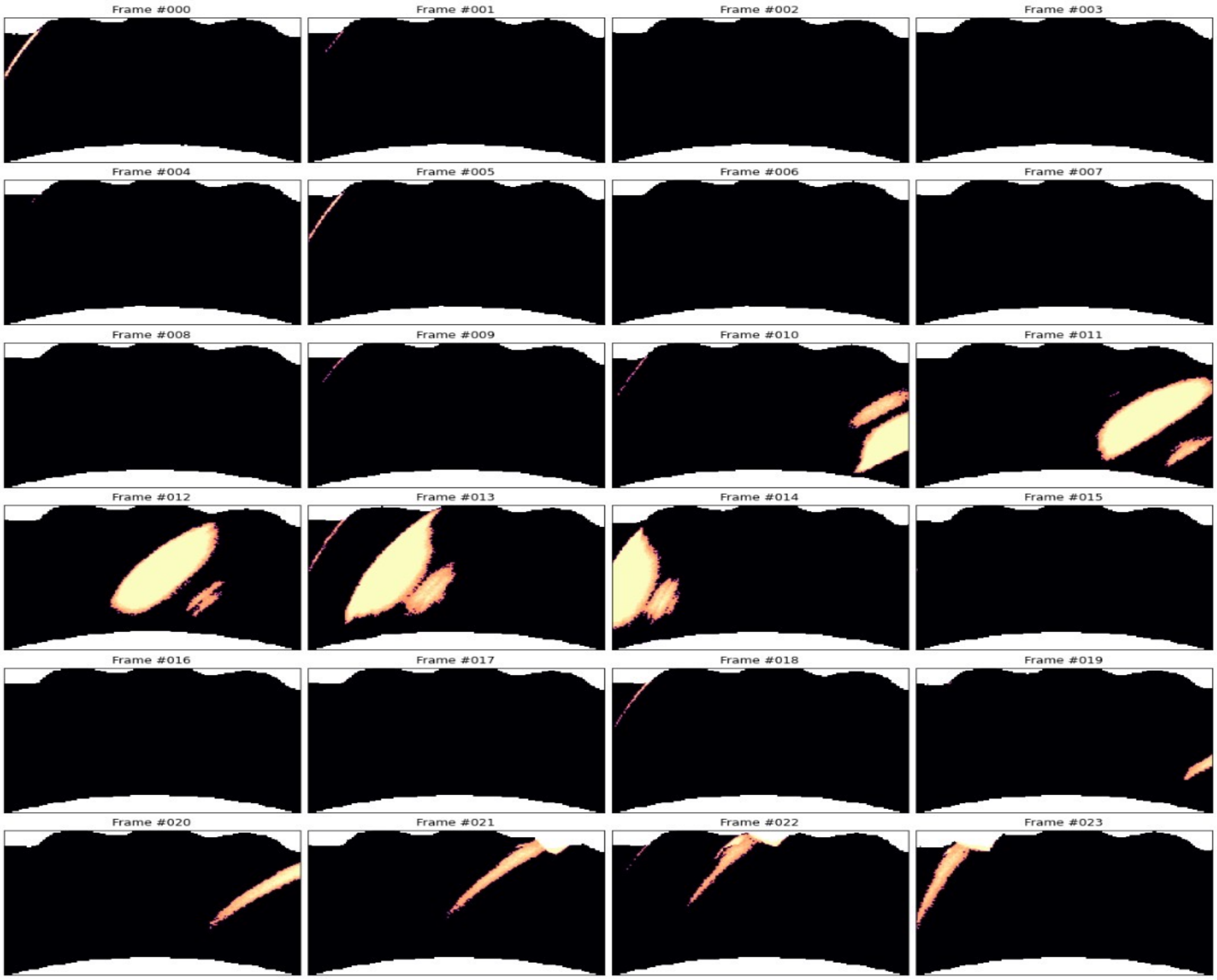

FIGURE 9. Sequence of Frames Captured by iPhone 13 Pro's TrueDepth Sensor

Figure 10 presented is a collage of multiple depth map frames captured using the iPhone TrueDepth sensor, each labelled sequentially (e.g., "Frame #000", "Frame #001", etc.). These frames form a comprehensive visualization of the depth data captured over a period, showing the gear's surface and its topographical changes. The arrangement of frames in a grid allows for clear observation of the progression of depth data captured over time. This sequential arrangement is particularly useful in identifying patterns or anomalies in the gear's surface, as it enables a continuous and dynamic view of the changes occurring in the gear's topography.

Depth values are represented per frame and the color map used to illustrate them is 'veridic', in which different depths are shown using colors. The greener the color, the shallower the areas, and the darker green, the deeper the areas. The importance of color-coding is that it allows to immediately understand changes in depth between the frames, thus quickly highlighting inconsistencies and potential anomalies. Like the single frames, these frames also show dead zones (white regions) and dead pixel (edge). Such artifacts are intrinsic to the constraints of the TrueDepth sensor and repeatable across multiple frames.

The areas on the body where the gear is mounted appear in different depths. This detailed image representation provides data that makes it possible to detect subtle changes of the gear surface including potential deformations during the service life. It is useful for identifying areas of which the engineering structure may be affected by deformations and, as such, visualizing these depth variations is very important to the anomaly detection process. By looking at frame to frame sequence, any inconsistencies where anomalies or distortions get introduced over time can be observed. These changes can be identified by looking at the differences between depth values in different frames and are imperative to correctly recognizing and then tracking anomalies.

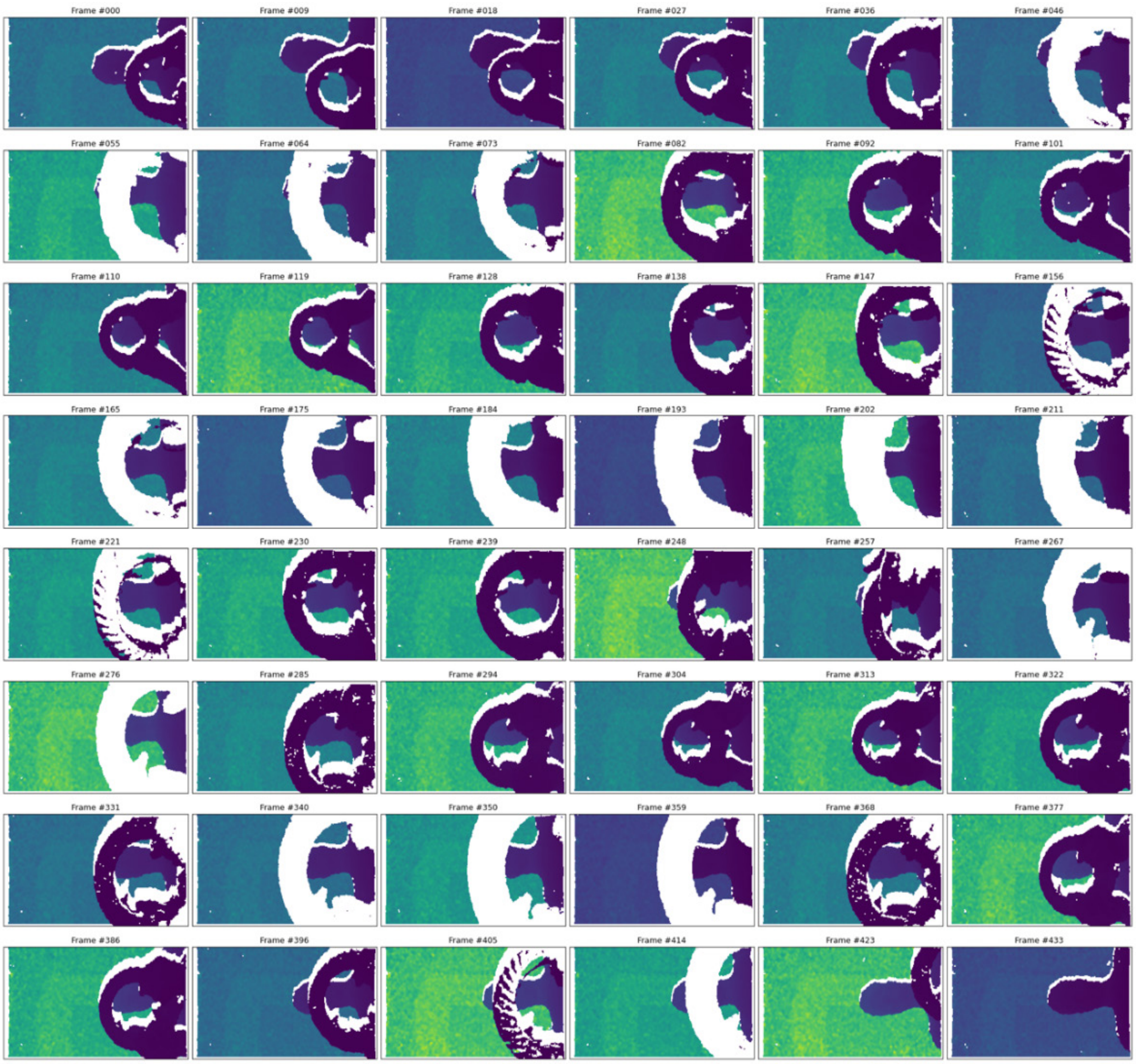

FIGURE 10. Sequential Depth Map Frames Captured Using iPhone TrueDepth Sensor

Figure 11 is a Depth map of "Frame #120" taken from iPhone TrueDepth sensor shown using a modified colormap range [0.1585, 0.18]. The image dimensions are 640x360 pixels and the depth values are encoded in Float32. Coincidentally, this plots the teeth of a gear much more visible and useful colour scales with depth reveal even further nuances than in other figures. Select the range of this colormap by trial and error to most sensibly show the gear teeth. The higher portions represent shallower areas of the gear, while the darker regions show deeper parts of the gear. This enhanced visualization helps to find specific topographical features and possible anomalies on gear flanks.

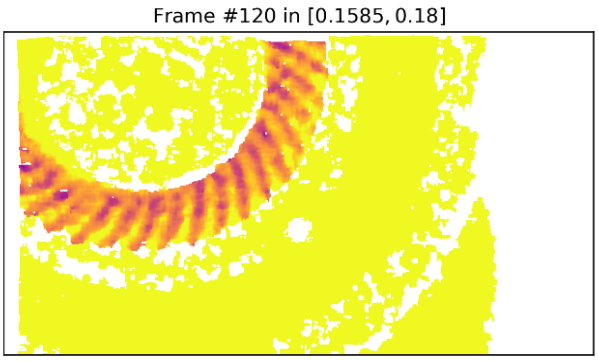

FIGURE 11. Depth Map Frame #120 Captured Using iPhone TrueDepth Sensor with Enhanced Colormap

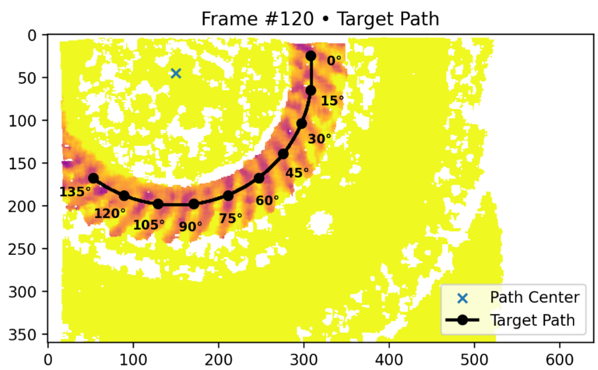

FIGURE 12. Depth Map Frame #120 with Elliptical Target Path Captured Using iPhone TrueDepth Sensor

Figure 12 shows the depth map "Frame #120" captured using the iPhone TrueDepth sensor, overlaid with an elliptical target path for detailed analysis. The frame dimensions are 640x360 pixels, and the depth values are encoded in Float32 format. The visualization uses the 'plasma' colour map within an enhanced range of [0.1585, 0.18] to highlight the gear teeth's details. The elliptical path, starting from the bottom left and ending at the top right, is marked with degrees for precise reference. The path center is indicated by an 'X' marker, and the path itself is highlighted in black with markers every 15 degrees. This visualization aids in understanding the gear's topographical features along the specified path, allowing for a focused inspection of potential anomalies and deformations on the gear surface.

Figure 13 illustrates the depth profile along an elliptical target path for "Frame #120" captured using the iPhone TrueDepth sensor. The x-axis represents the angle in degrees along the elliptical path, starting from the defined starting angle (θ_{start}) and progressing to the ending angle (θ_{end}). The y-axis denotes the depth values within the range of [0.1585, 0.18] meters.

The depth profile shows a sawtooth pattern corresponding to the gear teeth, with peaks and troughs representing the varying depths of the gear surface. Shaded areas indicate the gear body, while white regions highlight sections with NaN values where the sensor failed to capture depth. Red regions indicate closer distances to the sensor. This detailed depth profile aids in identifying specific topographical features and potential anomalies along the gear's elliptical path, providing crucial insights for anomaly detection and gear deformation analysis.

Figure 14 illustrates the graph of the depth profile along a predefined path on the gear's surface. The depth measurements, represented by the blue line, show fluctuations corresponding to the gear teeth's profile, with peaks and valleys indicating the high and low points. The red highlighted section denotes NaN values where the sensor failed to capture depth information. This detailed profile is crucial for assessing the precision of the depth sensor and identifying areas requiring calibration or data interpolation.

Figure 15 shows a series of images which utilizes a colormap to represent depth values, with different colors indicating various depth ranges. The colormap enhances the visibility of subtle depth variations and clearly highlights the structural features of the gear, facilitating the identification of geometric details and potential defects.

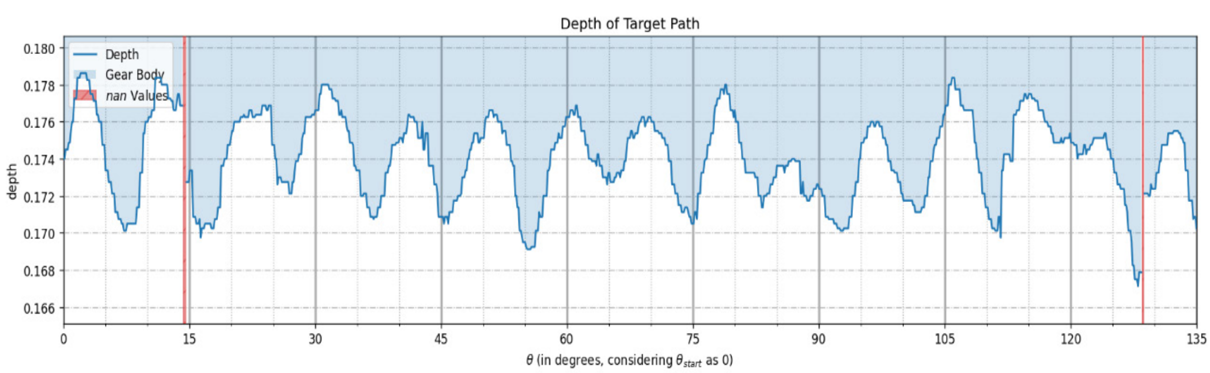

FIGURE 13. Depth Profile Along Elliptical Target Path for Frame #120 Captured Using iPhone TrueDepth Sensor

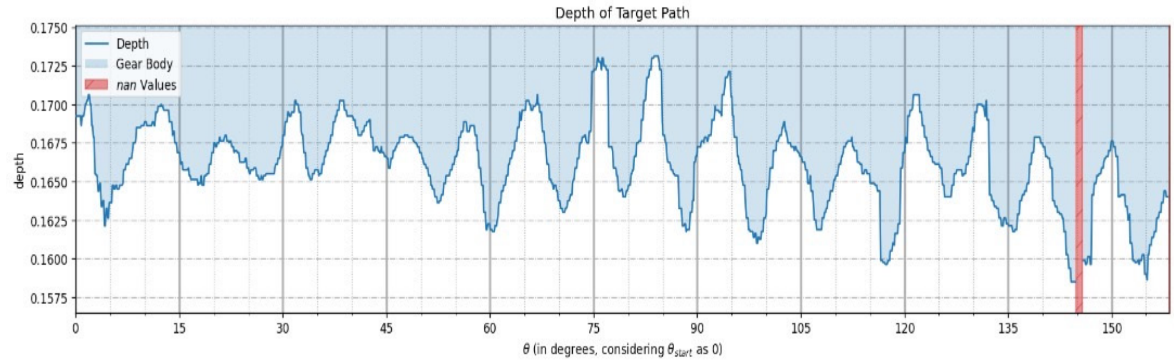

FIGURE 14. Depth Profile Along the Target Path.

Furthermore, Figure 16 is provided to concentrate on Frame #040, visualized within a specific depth range [0.1585, 0.174] to highlight the gear teeth. By narrowing the depth range, the details of the gear teeth become more prominent, thus improving the visibility of fine features. In this visualization, the yellow areas represent the background, while the purple areas indicate the gear's surface, creating a stark contrast that aids in clearly identifying the gear teeth. Visualizing data within a targeted depth range is essential for focusing on specific features, thereby enhancing the analysis of the gear's structural integrity.

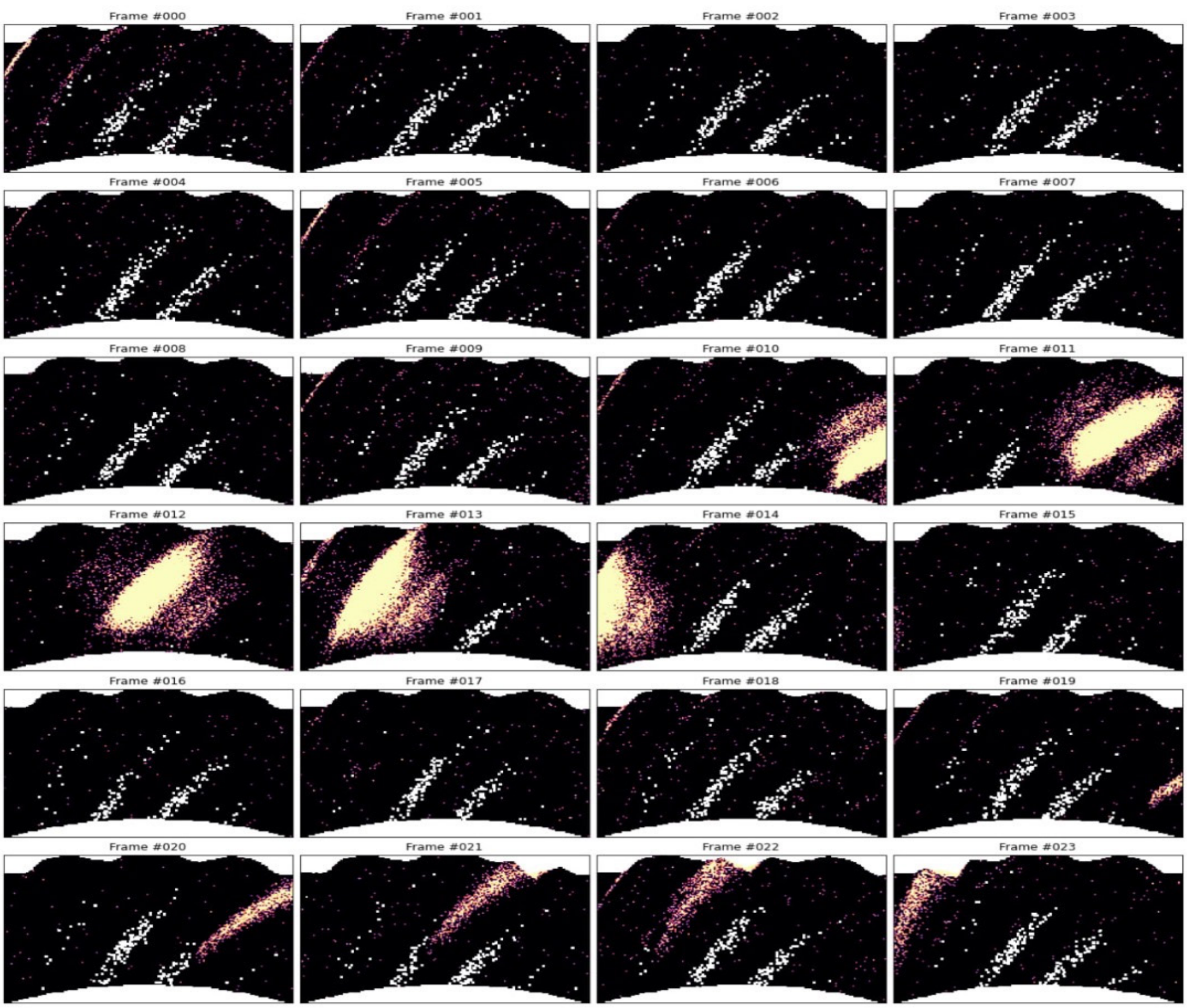

FIGURE 15. Frames Visualized Using Colormap

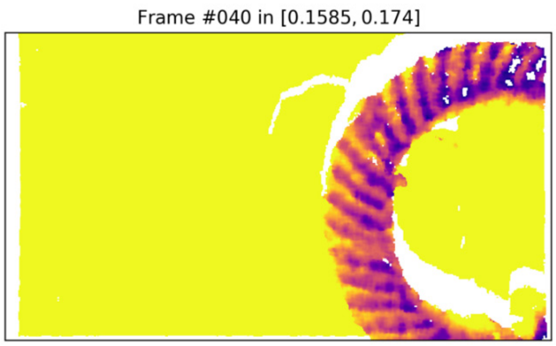

FIGURE 16. Visualization of Frame #040 within a Specific Depth Range [0.1585, 0.174]

This image highlights the gear teeth by focusing on a narrowed depth range, where yellow represents the background and purple indicates the gear's surface. This visualization enhances the visibility of fine structural features, aiding in the precise analysis of the gear's integrity.

DETECTION OF DEFORMATIONS

The confusion matrix is the central evaluation for testing the performance of the deformation detection algorithm. It shows the accuracy of classification as deformed vs non-deformed for real and predicted frames processed by the system. The matrix consists of four key elements: True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN). That 14 in the bottom right cell is simply the number of frames which were correctly classified as deformed, or true positives. The top left cell (94) indicates the number of total frames that were correctly predicted as nondeformed (true negative). The top-right cell (0) represents the number of frames incorrectly identified as deformed when they were non-deformed, representing the false positives. Finally, the bottom-left cell (0) denotes the number of frames incorrectly identified as non-deformed when they were deformed, representing the false negatives, Figure 17.

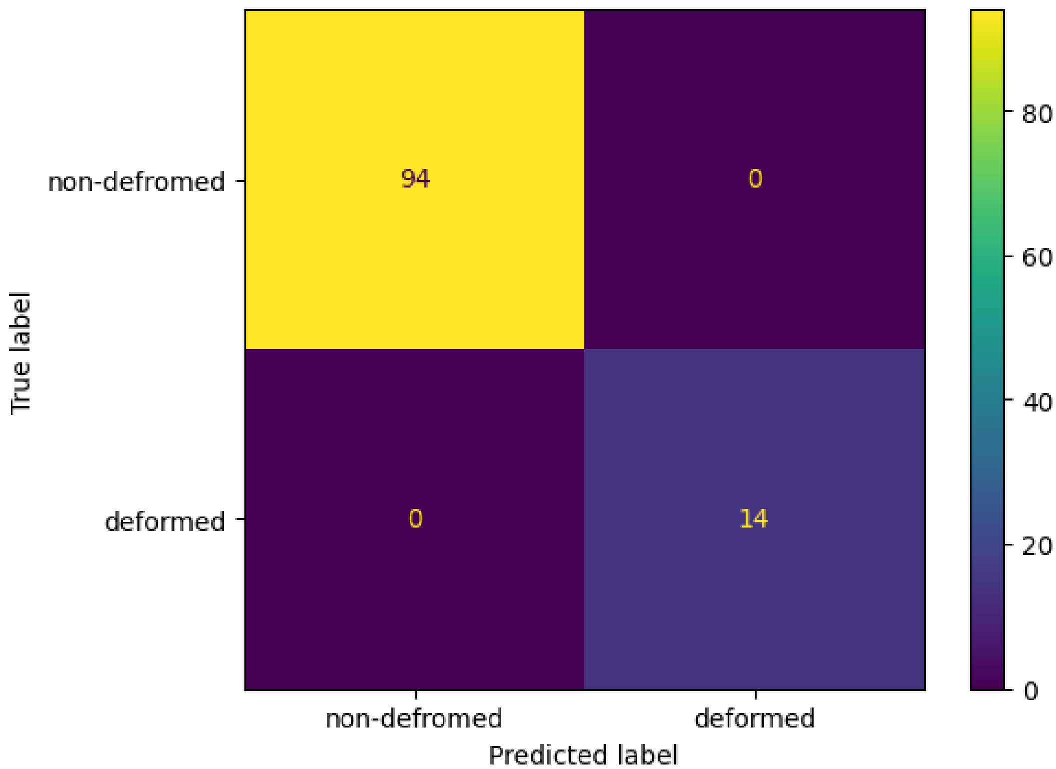

FIGURE 17. This confusion matrix visualizes the classification results of a model distinguishing between non-deformed and deformed gears

The matrix shows that all 94 non-deformed instances were correctly classified, and all 14 deformed instances were also accurately identified, indicating a perfect performance with no misclassifications.

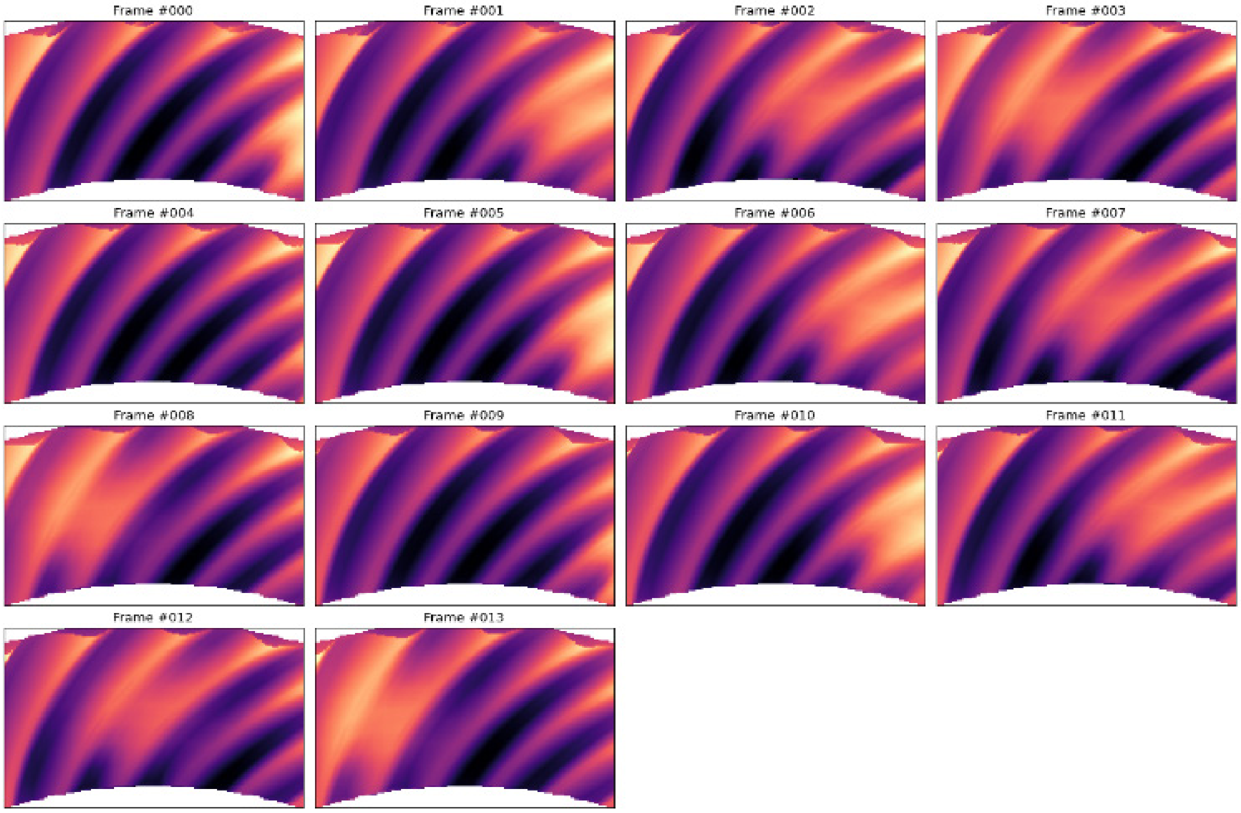

FIGURE 18. Illustrates 14 frames have deformation

Figure 18 depicts the detection of 14 frames exhibiting distortion out of the total frames analysed. In this illustration, the dark purple regions represent areas without distortion, with varying shades denoting depth. Conversely, the light orange areas highlight the distorted regions, providing a clear visual differentiation between undistorted and distorted segments.

Interpreting this matrix reveals several key insights. The overall accuracy of the detection algorithm is high, as indicated by the high values in the true positive and true negative cells. With 94 true negatives and 14 true positives, the algorithm demonstrates a strong ability to correctly classify both deformed and non-deformed frames. by applying equations (1, 2, 3, 4 and 5) Accuracy, Precision, Recall and F1 Score metrics, which can be derived from the confusion matrix, are both perfect in this case (Chicco & Jurman 2023). Precision, the ratio of true positives to the sum of true positives and false positives, is 1.0 = (14/(14+0)).

A precision of 1.0 (or 100%) means that every time the model predicts a positive class, it was correct. Therefore, there were no false alarms or incorrect positive predictions. A precision of 1.0 is ideal, as it indicates the model makes no false positive errors. However, precision alone does not tell the whole story about model performance, it needs to be considered alongside other metrics like recall, which measures how well the model identifies all relevant positive instances (true positives). Recall, the ratio of true positives to the sum of true positives and false negatives, is also 1.0 = (14/ (14+0)). A recall of 1.0 (or 100%) means that the model successfully identified all positive instances in the dataset. In other words, there are no false negatives, meaning the model did not miss any true positives.

A recall of 1.0 is ideal, as it indicates the model captures every relevant positive instance (Grasso, Remani et al. 2021). F1 Score is 1.0, = 2× (1.0×1.0)/ (1.0+1.0). The F1 Score is a metric that combines precision and recall providing a single measure of a model's performance, An F1 score of 1.0 is the best possible score, indicating that the model performs perfectly in terms of both precision and recall. This means the model is highly accurate and balanced in its ability to correctly detect positive instances without misclassifying negatives as positives. This perfect balance is especially important when precision and recall are equally critical, such as in sensitive detection systems where both false positives and false negatives need to be minimized.

Accuracy is used to calculate the accuracy of a classification model. It measures the proportion of correct predictions (both true positives and true negatives) out of all predictions made. Accuracy is 1.0 = (14+94)/(14+94+0+0), High Accuracy (closer to 1 or 100%) means that most predictions made by the model were correct (Chicco & Jurman 2020).

Additionally, specificity, which measures the proportion of actual negatives that are correctly identified, is perfect with a value of 1.0 (94/ (94+0)). Specificity measures how well the model correctly identifies negative cases. In other words, it tells how accurately the model can identify instances that should be classified as negative. A specificity of 1.0 means the model perfectly identifies all actual negative cases, without making any errors by classifying negative cases as positive. Thus, specificity is perfect in this case because there were no false positives (0), so all negative instances were correctly identified.

The color coding in the confusion matrix provides a visual representation of the performance, with brighter colors indicating higher values, helping to quickly identify the areas where the algorithm excels and where it may need improvement. The matrix shows that all 94 non-deformed instances were correctly classified, and all 14 deformed instances were also accurately identified, indicating a perfect performance with no misclassifications. Overall, the confusion matrix indicates that the deformation detection algorithm is highly effective, with perfect scores in key performance metrics, suggesting robust performance in distinguishing between deformed and non-deformed frames. Figure 19 shows deformation detectors evaluation between pixel-wise and frame-wise.

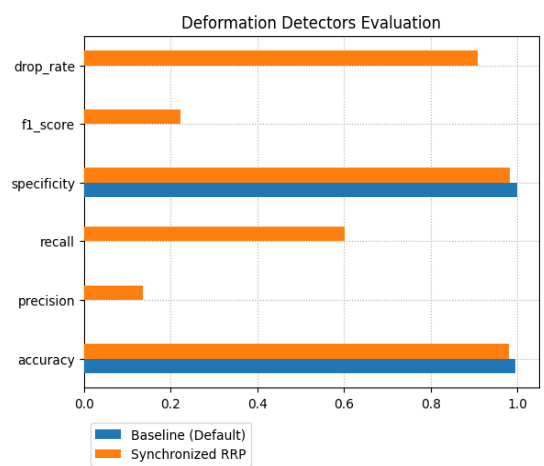

FIGURE 19. Deformation detectors evaluation

Table 2 shows the comparison of performance metrics between pixel-wise and frame-wise approaches for deformation detection. This table presents a comparison between pixel-wise and frame-wise approaches based on various performance metrics. Here's a breakdown of each metric in the context of this comparison. Accuracy in Pixel-wise is 0.972654 and at Frame-wise is1.0, Accuracy measures how often the model correctly identifies both positive and negative instances. The frame-wise approach has perfect accuracy (1.0), while the pixel-wise approach is slightly lower at approximately 97.27%.

TABLE 2. Comparison of Performance Metrics Between Pixel-wise and Frame-wise Approaches for Deformation Detection

Metric	Pixel-wise	Frame-wise
Accuracy	0.972654	1.0
Drop Rate	0.909245	0.0
F1 Score	0.306358	1.0
Precision	0.218780	1.0
Recall	0.510854	1.0
Specificity	0.978178	1.0

Drop Rate in Pixel-wise is 0.090245 and Frame-wise is 0.0, the drop rate likely indicates the proportion of instances that the method fails to detect. A drop rate of 0.0 for the frame-wise approach suggests it has no missed detections, whereas the pixel-wise approach has a drop rate of about 9.02%. F1 Score in Pixel-wise is 0.306358 and Frame-wise is1.0, the F1 score is the harmonic mean of precision and recall, providing a balance between the two. The frame-wise approach achieves the perfect F1 score of 1.0, indicating excellent precision and recall, whereas the pixel-wise approach has a much lower F1 score (around 0.31).

Precision in Pixel-wise is 0.218780 and Frame-wise is1.0, Precision measures the ratio of true positive detections to the total number of positive predictions. The frame-wise method has perfect precision (1.0), meaning all its positive detections are correct. The pixel-wise approach has low precision (approximately 21.88%), suggesting a high number of false positives. Recall in Pixel-wise is 0.510854 and Frame-wise: 1.0, Recall measures the proportion of true positive cases that the model correctly identifies. The frame-wise approach again has perfect recall (1.0), indicating it successfully detects all relevant instances. The pixel-wise approach has moderate recall (around 51.08%). Specificity in Pixel-wise is 0.978178 and Frame-wise: 1.0, Specificity measures the ratio of true negatives to the total number of actual negatives, indicating how well the model avoids false positives. Both approaches perform very well, with frame-wise reaching perfect specificity (1.0) and pixel-wise having a high specificity (approximately 97.82%).

As mentioned above, the frame-wise approach significantly outperforms the pixel-wise approach across all metrics, achieving perfect scores in accuracy, F1 score, precision, recall, and specificity. The pixel-wise method, while still reasonably accurate and specific, struggles with lower precision and recall, indicating it may produce more false positives and miss some true positives. This suggests that the frame-wise approach is more reliable for deformation detection in this comparison.

CONCLUSION

This paper presents an innovative approach to deformation detection by utilizing advanced imaging technology. Incorporation of the TrueDepth sensor from an iPhone 13 Pro for depth capture highlighted a cheap and novel approach to high-resolution acquisition for gears surfaces. The advantage of this method is that it can achieve both high resolution and easy use, which enables more sophisticated deformation detection to be used practically for many applications. The use of readily available technology such as a smartphone opens new possibilities for cost-effective and portable monitoring in industrial and engineering contexts.

The approach presented in this paper provides a solid analysis of the deformation detection for spiral bevel gears. This allows repair or maintenance operations to begin for the helical gears after identifying how much these complex parts have been deformed. The combination of complex imaging technology and methods for repair signals progress in the ability to preserve critical components, especially within aerospace, automotive and manufacturing.

In conclusion the implementation of a specialized algorithm for processing depth data from mobile phone-based depth sensing cameras significantly improves the accuracy of deformation detection in spiral bevel gears compared to traditional visual inspection methods. For future works, AI can be used in detecting and monitoring faults in mechanical systems. Systems powered by AI can monitor sensors, imaging technologies, and other environmental data in real-time to automatically identify any faults or deformations in mechanical systems. These algorithms have the capability of pattern recognition, able to identify anomalies or deviations in performance data that can detect even the most subtle problems as they may be overlooked during human and conventional detection mechanisms.

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DECLARATION OF COMPETING INTEREST

None.

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