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Rough Surface Wear Analysis Using Image Processing Techniques

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Abstract: Due to the great interest of the automotive industry to quickly and systematically evaluate low wear quantities a new approach based on image processing is presented. By comparing the captured rough surface point cloud using optical interferometry before and after wear, the proposed algorithm was able to estimate the amount of volume wear and mass loss. The proposed algorithm has two main steps. In the first step, the 3D point clouds obtained before and after wear are mapped to 2D images, and conventional edge detection algorithms are applied. Keypoints are determined using the SIFT algorithm on both images (before and after the wear), followed by the use of the RANSAC algorithm to create a good 2D registration between both 2D images. In the second step an enhanced ICP algorithm is used to perform a 3D registration. The main advantage of this method is the visualization of the wear geometry provided by the wear topography. The proposed algorithm was tested and the results are presented.

Keywords: Point Cloud Registration, Image Processing, Rigid Transform, ICP, SIFT.

1. INTRODUCTION

Systematical and efficient micrometrical wear evaluation is appealing to automotive, mining and manufacturing industries since it represents the possibility of costs reduction by the reduction of durability test time. Wear can be evaluated using different methods and techniques that can be grouped into one of three categories (Whitenton and Blau, 1988): weight loss, 2D analysis and 3D analysis. The weight loss method usually uses a microbalance to measure the specimen weight, before and after wear. Then the weight loss is calculated as the difference of the two measurements. However, this method can quantify only globally the worn material, while it cannot provide local information on the worn surface geometry. Furthermore, it cannot be applied for large or heavy specimens. 2D analysis provides only a section topology of the worn material, and therefore mass loss cannot be calculated from the measurements. The 3D analysis provides the worn material topography, the spatial identification of the wear zone can be also used to compare the surface topographic changes, and thereby calculate the wear volume and mass of the surface (Dong and Stout, 1995). For the 3D analysis, the surface topographic change comparison can only be performed after a 3D registration. Therefore, the goal is to find the transformation which aligns the common area of the surface before and after the wear process occurrs.

Recently Obara reviewed several well known methods to evaluate micrometrical wear based on 3d analysis (Obara and Sinatora, 2016). Most of the methods are based on wear quantification by comparing surface roughness parameters, such as the abbot-firestone and volume parameters, which are obtained from the surface topography according to ISO 25178-2:2012 (Jeng et al., 2004; Pawlus, 1997). He proposed a new method, also based on roughness parameter analysis which is more accurate than the previous ones. However, as the own author states, it cannot be indiscriminately applied due to assumptions that must be made related to the height references (Z coordinate) among two samples. Therefore, the objective of the present work is wear evaluation of a rough surface based on a full 3D point cloud analysis that allows one to verify the surface topographic changes, instead of topographical

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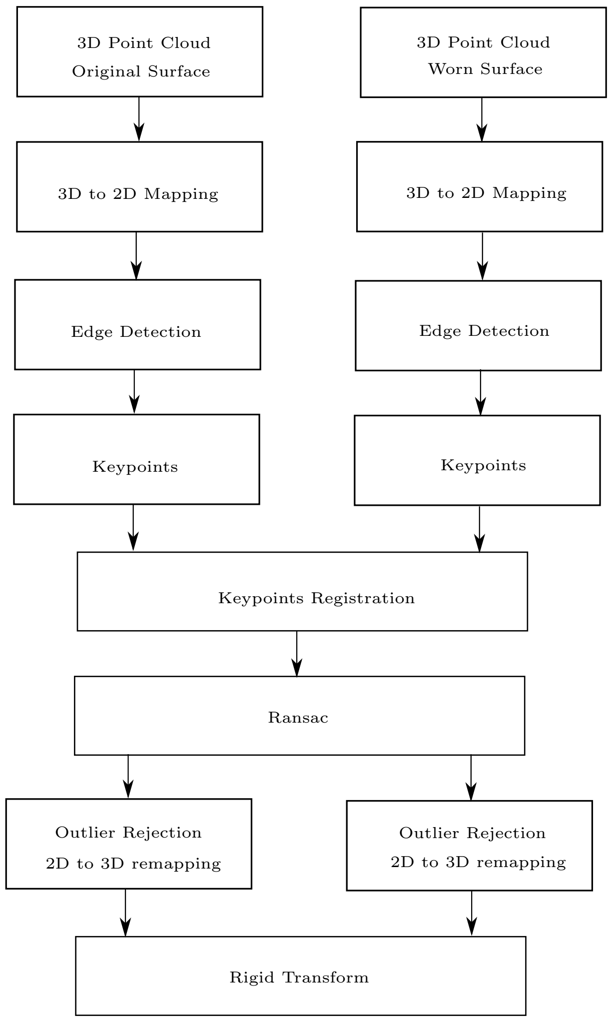


Fig. 1. Proposed Algorithm for rough surface comparison.

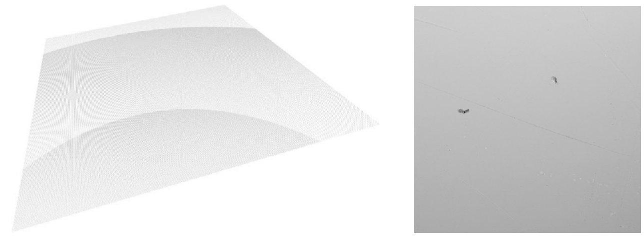
parameters. The surface comparison is performed by the point cloud registration followed by image processing techniques to identify the keypoints. The proposed algorithm was tested, allowing the wear visualization and the weight loss estimation.

2. PROPOSED METHOD

The algorithm proposed for rough surface comparison is depicted in Fig. 1. Two point clouds are captured (before and after the wear) using optical interferometry. Afterwards 2D images are created to intensify the key points that will be used to estimate a rigid transformation for registering the 2D images. In the final stage, the Iterative Closest Point (ICP) algorithm is used to register the captured 3D point clouds.

2.1 3D Point Cloud to 2D image mapping

The rough surface comparison algorithm has an initial process to provide a better visualization of the wear through the use of a 2D image. In this 2D image, the point cloud Z axis is represented by the gray scale levels, while the point cloud X and Y axis are values related to the image size. Fig. 2 shows 2D image obtained from the 3D point cloud. The 2D image clearly presents more details of the surface wear when compared to the 3D point cloud.



(a) (b)

Fig. 2. (a) Rough Surface 3D point cloud (difficult wear detection). (b) 2D image generated from the point cloud (difficult wear detection).

2.2 2D image Key Points identification

The 2D image usage provides a simpler keypoint identification from a point cloud. One of the approaches to register 2D images is by identifying certain distinctive features such as sharp edges, corners, contours, etc. Among the methods to identify distinctive features, the edge-based and the keypoint-based methods are quite useful and complement each other as shown by Pressigout and Marchand (2006); Choi and Christensen (2010); Vacchetti et al. (2004). Pressigout and Marchand (2006) combines a classical model-based approach based on the edge extraction and a temporal matching relying on the texture analysis. Choi and Christensen (2010) combined a keypoint based matching and an edge-based tracking. Moreover, as mentioned by Vacchetti et al. (2004), the incorporation of an edge-based method with a corner point-based method makes the system more robust and jitter free. As shown in Fig. 1, the proposed algorithm uses an edge detection combined with the determination of keypoints along the edge.

Edge Detection: Since edges in an image represent a discontinuity or significant variation in intensity or gray levels, edge detectors main objective is the identification and location of sharp changes in the brightness level (see Fig. 2b).

The Sobel edge detector (Sobel and Feldman, 1968) is a discrete differentiation operator that uses two 3×3 kernels to estimate the gradient in the x-direction and in the y-direction. Since the image is convolved with both kernels to approximate the derivatives in horizontal and vertical, the sobel kernels respond to horizontal and vertical edges. The Sobel is a very simple method that provides an approximation to the gradient magnitude. Another advantage of the Sobel operator is the detection of edges and their orientations. However, there exist some disadvantages of the Sobel edge detector method: it is noise sensitive. The magnitude of the edges degrades as the level of noise presented in image increases. As a result, Sobel operator accuracy worsens as the magnitude of the edges decreases.

The Canny edge detector (Canny, 1986) uses a filter based on the first derivative of a Gaussian filter and classifies a pixel as an edge if the gradient magnitude of the pixel is larger than those of pixels at both its sides in the direction of maximum intensity change. This gaussian filter reduces the noise, presents good performance to detect edges, it has fine positioning performance and low frequency response