

Defect Detection in Indirect Layered Manufacturing

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ABSTRACT

Direct Layered Manufacturing (LM) is an additive manufacturing process where part is built layer by layer based on its CAD file. Indirect LM is a process where mold for a part is built by direct LM process. In this work we demonstrate a machine vision setup for surface voids detection which can be used for surface quality inspection of parts built by indirect LM and certain direct LM techniques.

INTRODUCTION.

During last twenty year the use of Machine vision for Industrial inspection applications has progressed enormously. At the beginning its growth was constrained by considerably high computational requirements of image processing. But recently, due to the extreme advances in computer technology and also dramatic decrease of computer prices, machine vision systems has become more and more affordable and popular. Now they are intensively used in industry, significantly increasing the quality of manufacturing processes.

Basic advantages of machine vision for inspection applications are obvious: possibility of work in hazardous environment, non-destructive process, and high precision. There have been a number of successful applications of machine vision for inspection of surfaces of aircraft bodies [1] and engines [2], technical ceramics

[3], textile fabrics [4], lace [5], semiconductor wafermaps [6], etc.

Layered Manufacturing (LM), or Solid Free-Form Manufacturing (SFF), which is a new area in Rapid Prototyping, has been widely explored recently. LM process starts with a 3-D CAD model of a part. Currently industrial standard for the CAD data is .STL format, the collection of triangular facets, representing the surface of the object. Then, CAD model is sliced into a set of 2-D contours by intersecting it with set of horizontal planes. Next step is the toolpath generation – filling the interior of each slice by lines of different patterns: contours and rasters. At the fabrication stage, material is deposited from the liquefier, following the toolpath, layer by layer. The width of each deposited road depends on the width of liquefier nozzle, material type and parameters, etc. First, the boundary for each layer is fabricated following the contour curve to achieve a better smoothness. Then, the interior is filled by raster. Commonly, parts are fabricated with 90° alternating rasters between consecutive layers which results in a stronger part [7]. However, for some applications (e.g. piezoelectric actuators) quite different tool-path generation methods can be used. In indirect LM process the mold is built using direct LM technique and part itself is produced filling this mold.

It can be easily seen that errors in each layer in direct LM process can be and must be detected and fixed before going to consecutive layer. For some complicated

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parts LM process can take many hours, and for some materials, e.g. ceramics, even a small number of defects can be critical and can lead to a defective part. Hence, quick and precise quality inspection of each layer becomes very important step in the direct LM process. Machine Vision seems to be the best candidate tool for this inspection. Using optical sensing one will be able to monitor each layer after it is built and before the next layer is deposited, detecting defects and feeding back their location and size information to machine in order to correct them. The precision of optical equipment and affordability of CCD cameras make this application quite reasonable and promising. In indirect LM process surface inspection can also be very useful. In some applications, quality check of the mold and surface check of the part itself may be necessary. Also, for some materials used surface structure of part can reflect its bulk texture, which makes surface inspection extremely important step in the determination of part quality.

We studied square ceramic samples and experimental wrench sample. Green ceramic samples were fabricated of PZT (piezoelectric ceramic) powder with binder using direct LM technique with zero offset between raster roads, i.e. offset between any two tool-path raster roads was set equal to single road-width. Thus, each actual raster road was supposed to touch the adjacent roads, and any surface voids were not supposed to occur. Raster and contour roads were designed to overlap. Therefore, any voids on the surface can be characterized as defects, and voids detection, performed on each layer, would significantly increase the resulting quality.

Wrench sample was fabricated of metallic powder with binder by indirect LM technique. Assuming uniformity of its structure, we can say, that the distribution of voids on the wrench surface is similar to one in its volume. Hence, performing surface inspection on green sample of wrench would be helpful in determining its quality, which is rather important for hard tools.

MACHINE VISION SETUP.

Machine Vision setup used in our study is schematically shown on Fig.1. PULNIX TM-9701 CCD camera with NAVSTAR optical magnifying and polarizing equipment was set vertically. FOSTEC A20520.2 lighting setup was used to illuminate the sample surface. Two optical fiber goosenecks with polarizing caps were used as a beam light sources, directed at small angle to surface ($\sim 10^\circ$) to make surface voids appear distinctly on the image by double shading them. (Fig.2.) This lighting setup is similar to ones used in [1], [3]. Polarized light was used when inspecting ceramic samples to remove glares caused by direct reflection and obtain "smoother" image. We could not use polarized light for wrench inspection because of higher light absorption coefficient of its material, significant light intensity loss during polarizing and limited power of our light source.

Images were captured by μ Tech MV-2000 frame grabber board and saved as 640x480 uncompressed greyscale bitmap (.BMP) file, in which value of 0 corresponded to black color, 255 – to white color, and values between 0 and 255 – to intermediate levels of gray. Pixel size was set $10 \times 10 \mu\text{m}$ for ceramic samples, and to $15 \times 15 \mu\text{m}$ for wrench sample.

Single image captured by the camera contained only part of the sample surface, due to high precision requirements, constrained FOV (field-of-view) of camera and large sample size. Therefore, single images were to be mosaiced into one large image of the whole surface. In this work mosaicing was done manually by placing the samples onto positioning table and capturing images with certain horizontal and vertical shifts. In the on-line process mosaicing will be performed by positioning the camera, firmly attached to liquefier head, into certain points above the sample being built and capturing single images. Coordinates of these points can be calculated based on slice data and camera's magnification and FOV parameters. On-line mosaicing can be done with a rather high precision due to high precision of the LM machine positioning system. Also, no special sample-background segmentation was made, given that information about the slice contours would be provided in an on-line process.

IMAGE PROCESSING.

Image processing programs were written on MathWorks MatLab script using MatLab Image Processing Toolbox functions. Computations were performed on Gateway2000 E-3100 computer with Intel PentiumII 266 MHz processor and 64 Mb of RAM.

Before processing, image of wrench was enhanced. Due to "powder" structure of wrench material, direct reflection from some metallic particles appeared as small white spots, and absorption, presumably in interparticle microcavities, appeared as small black spots, forming "salt-and-peppa" noise on the input image. (Fig.3) Therefore, median filter with 7x7 mask was applied to remove this noise. (Fig.4) This filtering step was especially necessary since it removed a large number of small (1-3 pixel) black spots, which could be treated as defects and significantly slow down the following defect analysis.

As a result of double shading, voids appeared on the image as black spots, while the rest of surface appeared gray. Unlike other voids detection works [1], [3], where edge detection techniques were used to determine voids, we applied thresholding operation to form binary image containing voids (Fig.5) For wrench sample inspection light was calibrated to use fixed threshold value of 75, and for ceramic sample – of 55. All pixels of greyscale value of threshold and less, was assigned equal to 1 in binary image, and all others to 0. Automatic calculation of threshold by histogram [4] was not considered suitable in our application, since the number of pixels in black spots was significantly less than the number of gray pixels, and, hence, image histogram would not have two distinct peaks. Choosing threshold value by certain percentage of number of pixels having greyscale value less than threshold, was also not suitable, since the percentage of voids, and, therefore, black pixels, was not known.

For labeling, we defined an object as a set of pixels with values, equal to "1", where 4-connected (considering only two horizontal and 2 vertical closest neighbors) or 8-connected (considering also diagonal neighbors) neighborhood of each pixel contains pixels of

value "1". Labeling operation changes all "1" valued pixels of the specific object into specific number "n", where n starts with 1 for the first found object and increases by one for the next found object.

Since all objects are now different, we can now extract each object's features, such as size and location. First, we scan the image, storing the number of times each label value is found and the first and the last x- and y-coordinates it is found at, in an element of a vector $q[n]$, where q is the vector of certain characteristic. (size, etc.) It is seen at once that these vectors are very useful for the future analysis. Number of elements in the size vector is number of voids found, and we are now able to analyze the distribution of defect sizes. For example, the largest or the smallest void, or the number of voids of a certain size can be obtained easily and very quickly. Hence, for further operation with a certain voids, e.g., studying of a void shape, or generation of correcting tool-path, we narrow our work area from the whole image into a much smaller sub-image, which extremely decreases the processing time.

Fig.6 shows labeled voids with a size > 10 pixels. Centers of constraining rectangles are marked with circles. Figs.7-10 show the application of this detection technique to a sample made of ceramic material.

The structure of parts, fabricated by direct LM process with different parameters, may be significantly different than the ones studied in this work. For instance, parts built with positive offset parameter, have gaps between roads, which are made intentionally. These gaps would be wrongly detected as errors by our method. Also, setting negative offset parameter, i.e. overlap of adjacent roads, significantly decreases the risk of voids occurrence, but causes bumps along the raster roads due to double material deposition. These bumps can cause shadows, which would be detected as "false voids" by this technique. For these cases, different methods using texture approach and process signature analysis can be applied [8].

CONCLUSION.

Machine Vision setup has been designed for detection of surface defects (voids) in indirect and "zero-offset" direct LM process. Use of special lighting allowed exploring one-camera setup, which made inspection process much faster and more affordable. Computation efficient algorithms were designed and used for image processing.

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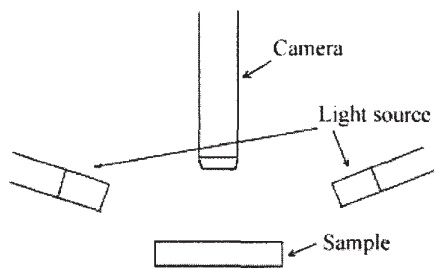


Fig.1. Schematic Machine Vision setup.

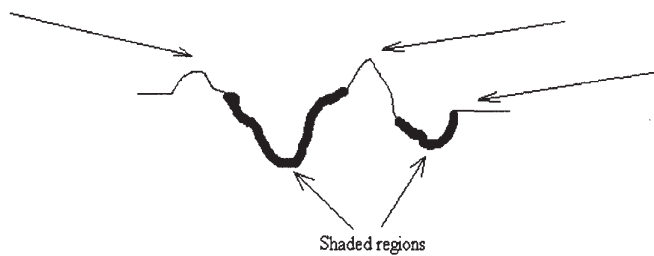


Fig.2. Double shading



Fig.3. Initial image of the wrench sample



Fig.4. Filtered image of the wrench sample



Fig.5. Image of voids of the wrench sample

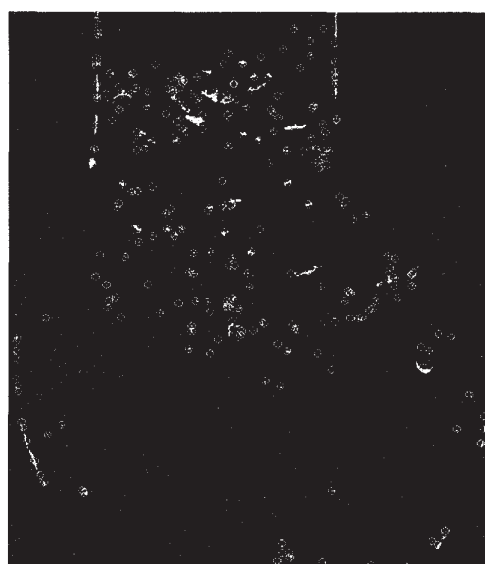


Fig.6. Voids location for wrench sample

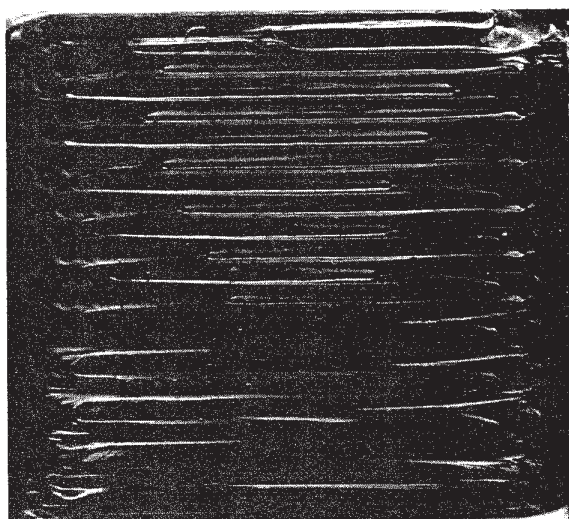


Fig.7. Initial image of ceramic sample

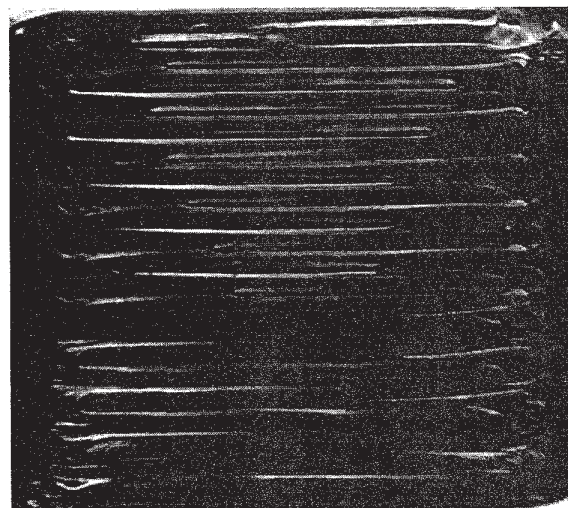


Fig.8. Filtered image of ceramic sample

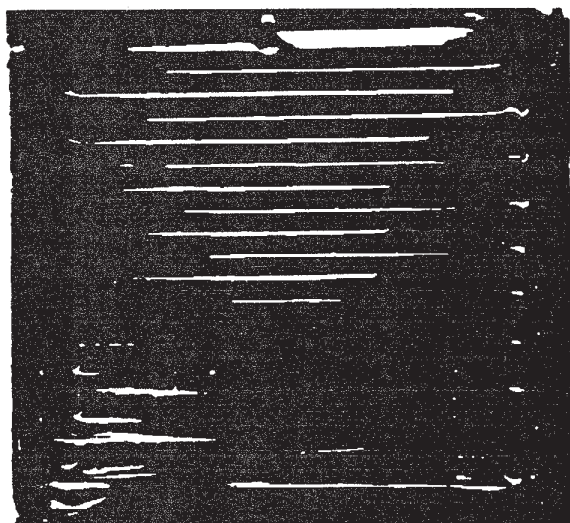


Fig.9. Image of voids of ceramic sample

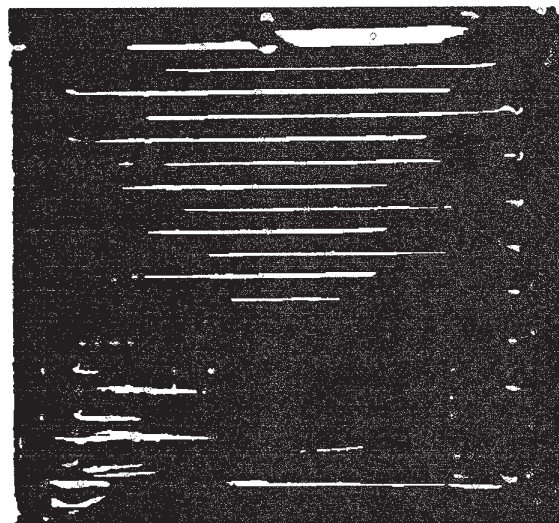


Fig.10. Voids location for ceramic sample