Title:

## CAD-based Calibration for On-machine Measurement using Vision

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## Introduction:

The development and monitoring of machining processes is an important challenge in the control of production cost and for the quality of machined parts. Integrating inspection procedures within the production process contributes to the automation of a production system. Significant benefits include high speed of inspection, measurement flexibility, on-machine inspection, capability, and the possibility of $100 \%$ inspection [3]. As far as on-machine inspection is concerned, it allows rapid decision making regarding the conformity of the produced part. This is in particular due to the great interoperability between machining and inspection. However, measurement operations and machining operations must be performed in the same reference frame to facilitate the comparison of the machined part to the CAD model for the conformity analysis. On-machine inspection is often performed using a vision based-system. Vision-based systems are used for the verification of machine set-ups [6], the survey of tool trajectories [1], part inspection of socket production, and so on [3]. These systems present various advantages: low cost, rapidity, flexibility and simplicity of implementation in the context of production. A minor drawback is the system calibration. Calibration is necessary to transform a 2 D point (or a point belonging to the picture) into a 3D point expressed in the reference frame. Within the context of on-machine inspection, the positioning of the camera frame relatively to the reference frame must be performed for each measurement operation. More generally, the reference frame of calibration can be anything. To enhance the interoperability between machining and inspection, it could be interesting that the reference frame or CAM frame, associated to machining operations, should coincide with the reference frame used for calibration. This removes an additional step of frame registration which is penalizing in terms of computational time and quality.


Fig. 1: On-machine inspection based on vision.

This paper deals with a CAD-based calibration method for on-machine inspection. Its originality is that the CAM frame is not only used to define the machining operations, but it is also the calibration reference frame and thus the measurement frame. For this purpose, the reference frame must be built from features of the machine tool scene. In the approach developed in this paper, features represented in the CAD frame are used to map the vision calibration frame to the machining frame in which both measurements and machining operations will be performed. As CAD-based calibration is performed at the beginning of the production, problems of coolants or removed chips/strings obscuring vision views are avoided.

## Main Section:

Based on the pinhole model, which is the most largely used, the calibration aims at identifying the model parameters that define the relationship between the coordinates of a 2D point, expressed in the picture $R_{p}$, and the coordinates of a 3D point expressed in the reference frame $R_{w}$. The relationship between $R_{w}$ and $R_{p}$ results from the combination of geometric transformations A.P.T as defined in Fig. 2. The matrix $A$ corresponds to the affine transformation from the center picture frame $R_{F}$ to the corner picture frame $R_{p}$. The transformation $P$ is a perspective projection of $R_{C}$ into the retinal plane $R_{r}$. The parameters associated with the matrix transformations $P$ and $A$ are called the intrinsic parameters (focal, pixel size and number, picture center position). Note that an additional transformation $D$, corresponding to the camera distortions, can also be taken into account. In this study, distortions are not considered.


Fig. 2: Pinhole model of a camera.
Finally, the transformation $T$ between the reference frame $R_{w}$ and the camera frame $R_{c}$, corresponds to a combination of a rotation $R_{\text {ave }}$ and a translation $t . T$ can be described thanks to a homogeneous matrix, and its parameters are called the extrinsic parameters (Eqn. 1).

$$
\left[\begin{array}{c}
X_{C}  \tag{1}\\
Y_{C} \\
Z_{C} \\
1
\end{array}\right]_{R_{c}}=\left[\begin{array}{c}
X \\
Y \\
Y \\
Z \\
1
\end{array}\right]_{R_{w}}=\left(\begin{array}{rr}
R_{3,3} & t \\
0 & 1
\end{array}\right) \cdot\left[\begin{array}{c}
X \\
Y \\
Z \\
1
\end{array}\right]_{R_{w}}
$$

Several techniques of calibration now allow the determination of extrinsic and intrinsic parameters simultaneously. Starting from point or line 2D-3D correspondences, most techniques are based on the minimization of a projection error function [4-5-7]. A few studies rely on the CAD definition of the studied scene to perform the calibration. In this direction, Beaubier et al. [2] proposed a CAD-based calibration using stereo-correlation. His approach does not rely on the final part but on the part during machining which possesses geometrical defects. Furthermore, the stereo-correlation requires a pattern projection which is not appropriate for on-machine inspection due to the low contrast, the difficulty to extract more than a few features, and it may be time consuming.

As the vision system is dedicated to on-machine part inspection, the new CAD-based calibration method proposed in the paper relies on identifiable geometric features of the machine tool scene. As aforementioned, the idea is to define a unique frame for calibration, vision-based measurements, and machining operations. For this purpose, the reference frame $R_{W V}$ is defined as the CAD frame in which machining operations are defined. It thus seems relevant to calibrate the system thanks to features or geometrical elements belonging to the machining set-up as they belong to both the CAD model and the machining environment, and as they are also not modified during machining. This will make the integration of the measurement in the machining process easier.

During on-machine vision, intrinsic parameters are fixed and do not vary. Therefore, the study focuses on the determination of the extrinsic parameters i.e. on the identification of the elements of the transformation $T$ (Eqn. 1). The proposed method relies on the use of features belonging to the machining set-up present in both the scene picture (picture of the machine tool environment) and the CAD model. The objective is to establish the correspondence between the 3D features (of the CAD model) and the 2D features (belonging to the picture). Once the correspondence is established, the transformation between $R_{p}$ and $R_{w}=R_{C A D}$ can be deduced, which leads to the transformation $T$ between $R_{c}$ and $R_{\text {CAD. }}$ Indeed, as the intrinsic parameters are well-known, the transformation $M=A . P$ between $R_{p}$ and $R_{c}$ is completely defined (Fig. 3).


Fig. 3: General purpose of the CAD-based calibration.
To establish the correspondence, 3D features of the machining setup should be recognized on the picture of the machining setup. It is important to notice that the set-up defects are neglected, and the actual machining set-up is assimilated to its CAD model. The idea is thus to use geometrical elements easily identifiable as displayed in Tab. 1. The table puts forward the 3D geometrical feature of the CAD model, the associated 2D element belonging to the 2D picture, and the extracted 2D element. The transformation $T$ is characterized by 6 parameters, 3 Euler angles for the rotation $R_{\mathrm{a} v \mathrm{E}}$ and 3 distances for the translation $t$.

| 3D feature (CAD model) | 2D feature (picture recognition) | 2D extracted element |
| :---: | :---: | :---: |
| Cylinder | 2 Cylinder generatrices | Line (bisector axis) |
| Sphere | Circle | Point (center) |
| Intersection of 2 planes | Line | Line |
| Circle | Ellipse | Point (center) |

Tab. 1: Features existing on the machining setup and identifiable on pictures.

The set of features must lead to a minimum of 6 independent equations to completely define the transformation. The choice of the set of features in number and positions is essential to ensure correct parameter identification. In Fig. 4, the degrees of freedom allowed for a line and a point are reported. Considering the degrees of freedom fixed by each feature, the method requires at least 3 points or 2 lines (non-coplanar in $R_{C A D}$ ).


Fig. 4: Degrees of freedom allowed for a line (a) and a point (b).

Starting from an initial value of the extrinsic parameters ( $R_{\text {init }}$ and $t_{\text {init }}$ in Fig. 5(a)), the 3D features of the CAD model are projected onto the picture frame. In parallel, equivalent 2D features are extracted from the picture (Fig. 5(b)). Let us consider the case of a point $C$ belonging to the CAD model. C is projected onto the picture frame $R_{p}$ in C' (by the combination of the transformation $T_{\text {init }}$ and the internal transformation $M$ ). The same goes for line $d_{C A D}$ belonging to the CAD model which is projected in $d_{\text {pict }}$ in the picture frame. In parallel, the elements are extracted from the picture: the point $D$ and the line $d_{\text {detect }}$ for the cylinder axis (Fig. 5(c)). It is thus possible to calculate the projection error for each type of feature. For points, the error is defined as the distance (Eqn. 2) in pixels between the extracted point and the projected point as represented in Fig. 5(c).


Fig. 5: Principle of the CAD-based calibration: (a) CAD features projected onto the picture, (b) Detected elements from the picture, (c) Projection error for the line and the point.

For lines, two errors are calculated corresponding to the distances of the most extreme points of the projected line $d_{\text {pict }}$ to the extracted line $d_{\text {detect }}$ (Eqn. 3).

$$
\begin{gather*}
e_{\text {point }}=d\left(C^{\prime}, D\right)  \tag{2}\\
\left\{\begin{array}{l}
e_{\text {axis }}^{1}=d\left(A^{\prime}, d_{\text {detect }}\right) \\
e_{\text {axis }}^{2}=d\left(B^{\prime}, d_{\text {detect }}\right)
\end{array}\right. \tag{3}
\end{gather*}
$$

For a set of $m$ lines and $n$ points, this yields to an error vector $E(\square)$ of dimension $2 m+n$ where $\square=$ $\left\{\varphi, \theta, \psi, \mathrm{t}_{\mathrm{x}}, \mathrm{t}_{\mathrm{y}}, \mathrm{t}_{\mathrm{z}}\right\}$ corresponds to the extrinsic parameters. The matching problem between 3 D features and

2D features, i.e. the calibration, leads to the minimization of the function $F=E^{T} \cdot E$. Thus, a first-order expansion of the error near the initial point $D_{0}$ is carried out:

$$
\begin{equation*}
E(\Phi)=E\left(\Phi_{0}\right)+\left[\frac{\partial E}{\partial \Phi}\right]_{\Phi_{0}} . d \Phi \tag{4}
\end{equation*}
$$

Note $A=\left[\frac{\partial E}{\partial \Phi}\right]_{\Phi_{0}}$ the Jacobi of $E$.
The problem is thus to find $\square$ so that $F$ is minimized. This gives:

$$
\begin{equation*}
\frac{\partial F}{\partial \Phi}=2 \cdot E^{T} \cdot \frac{\partial E}{\partial \Phi}=0 \tag{5}
\end{equation*}
$$

Considering the Jacobi of E , this yields to:

$$
\begin{equation*}
A^{T} \cdot E=0 \tag{6}
\end{equation*}
$$

Then:

$$
\begin{equation*}
A^{T} \cdot E=A^{T} \cdot\left(E\left(\Phi_{0}\right)+A \cdot d \Phi\right)=A^{T} \cdot E\left(\Phi_{0}\right)+A^{T} \cdot A \cdot d \Phi=0 \tag{7}
\end{equation*}
$$

And finally:

$$
\begin{equation*}
d \Phi=-\left(A^{T} \cdot A\right)^{-1} \cdot\left(A^{T} \cdot E\left(\Phi_{0}\right)\right) \tag{8}
\end{equation*}
$$

The approach is applied to the set-up presented in Fig. 3. The initial transformation $T_{\text {init }}$ is obtained by manual matching of 6 points defined in the CAD model. In parallel, the feature extraction from the picture is performed using the toolbox Image Processing of Matlab ©. After filtering the picture using the Canny filter, circles and lines are extracted from the picture thanks to the Hough transform. Then the optimization problem is solved thanks to the least-square method. Results are displayed in Fig. 6, in which yellow features correspond to the 2D extracted element from the picture, the red features correspond to the 3D elements projected onto the picture using the initial transformation $T_{\text {init }}$ and the green elements are the optimized elements solution to the least square problem.

The method allows the maximal error to be reduced by $80 \%$, assessing the relevance of the proposed approach for the optimization of the transformation $T$. Nevertheless, there are still deviations between the projected and the extracted features. This is in particular due to 2 main causes. The first one is that the set-up, which is assumed to be perfect, presents some defects that should be taken into account. Indeed, dimensions and positions of the components belonging to the set-up do not perfectly match their configuration of the CAD model. On the other hand, the method used to extract 2D features from the picture involves some errors. Indeed, the extraction is dependent on the quality of the picture but also on the parameters associated to the extraction method (nature of the filter, values of the thresholds ...). Both sources of errors have the same importance on the deviations. Therefore, in order to quantify the uncertainty associated to the proposed method of calibration, the influence of the feature extraction is investigated.


Fig. 6: Result of CAD-based calibration on geometric features.

The sensitivity study is conducted by considering that an uncertainty can be associated with the position and the orientation of the extracted element. For instance, an extracted 2D line is defined in the picture by its explicit model $y=a \cdot x+b$, where a represents the slope and $b$ the intercept. An uncertainty is thus associated to each parameter $a$ and $b$, and is modeled by a Gaussian distribution characterized by a standard deviation. The uncertainty associated to the CAD-based calibration is obtained thanks to 1000 Monte-Carlo simulations. Results bring out that the standard deviation of the maximal error does not exceed 0.0341 pixels. This shows the good stability of the CAD-based calibration method with regard to feature extraction. Indeed, the calibration error is probably due to the set-up defects: dimensions and positions of the components belonging to the set-up do not perfectly match their configuration of the CAD model.

## Conclusions:

In this study, we presented a CAD-based calibration method. Based on the CAD model of a machining set-up, this new technique is particularly well-adapted for on-machine part inspection, as it allows measurements in the manufacturing frame. It relies on the matching of 3D CAD-features of the machining set-up with corresponding features extracted from the 2D image. The first results show the relevance of the proposed approach, attested by the good stability of the method with regard to image analysis. In the future, we will focus on the choice of the features (position and orientation of the features in the picture and CAD frames) that are necessary to ensure the method's robustness.

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