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Machine Vision System for Positioning and Verification of Gas Oil Filters based on Eigenimages

Franci Lahajnar, Stanislav Kovačič
Faculty of Electrical Engineering, University of Ljubljana
Tržaška 25, 1001 Ljubljana, Slovenia
{franci.lahajnar, stanek}@fe.uni-lj.si

Abstract *A PC based machine vision system is described, designed for precise positioning and reliable recognition of gas oil filters. The system has been integrated into the production line, which is capable of assembling several types of filters, each one having its own visual appearance. Our primary goal was to design a flexible system, which could be easily adapted for assembling different filter types. To achieve this an appearance based method, employing the Karhunen-Loeve expansion, was used. Based on this method, the most significant visual information is automatically extracted from a set of rotated filter images, i.e. templates, and described by a small number of eigenimages. The eigenimages constitute the eigenspace. These templates and the captured image of the filter in an unknown position are projected to the eigenspace. The distances between the projected templates and the projected filter image are computed. Based on these distances, the filter position and its type are determined and the filter rotated. The system operates in a closed loop, therefore the new position can be evaluated and corrected, as required. The results obtained so far show that the system works reliably, and meets the required accuracy and speed.*

1 Introduction

Positioning and verification of parts in general is often required operation in the process of automated assembling of products in the industry. Precise positioning of parts simplifies design solutions of assembly lines, while verification of parts removes defective or spurious parts from the assembling process and in that way prevents from producing false products. For a manipulator, to be able to set an object into a preferred position in a precise and intelligent manner, it must rely on sensory feedback [1]. Feedback provides information that can enable a manipulator to handle with objects in its workspace. In the past, feedback was mostly based on mechanical approaches. Those kind of devices are usually manufactured for positioning a particular part. Because of their construction even a small modification of part requires the device modifications as well. Therefore, usage of mechanical positioning devices is not suitable if parts, which need to be positioned, are often modified. In cases like ours, the positioning device has to be designed such that modifications of parts at least to some extent, does not require major modifications of the positioning device. This is difficult and in some cases even impossible to achieve if mechanical techniques are applied. On the other hand, contactless, e.g. machine vision based systems are proven to be more efficient.

Traditionally robot vision systems have relied on shape models [2]. However, in the last few years several appearance based approaches were proposed. Approaches can be broadly classified into two categories: feature based and learning based. The methods in the first category use image features to find the rotation and translation of the object. Most frequently used features are geometric primitives, e.g. edges, lines, corners, and circles [2, 3, 4, 5]. Many of these methods require prior calibration of the sensor's intrinsic parameters, e.g. focal length as well as its extrinsic parameters, e.g. rotation and translation with respect to the manipulator. The second category of methods includes a learning component. In the learning stage, the mapping between image features and manipulator coordinates is derived. This mapping is then used in positioning stage. This is generally accomplished without any knowledge about the object's geometry or the manipulators's kinematic parameters (e.g. [1, 6, 7, 8, 9, 10, 11]).

In this paper we describe a machine vision system (MVS) developed for rotational positioning and type verification of gas oil filters. The goal was to design a flexible system capable of positioning and recognition of various types of gas oil filters, as presented in the next section. The task has been solved by machine vision techniques that are described in Section 3. For that purpose an appropriate imaging system setup has been selected, algorithms based on Karhunen-Loeve transorm have been developed and adequate hardware configuration has been chosen. The MVS for positioning and inspection of gas oil filters has been integrated into the assembly line. The results, which are shown in Section 4, prove that the system operates reliably and accurately.

2 Problem description

Gas oil filters are cylindrical objects with length of about 120 mm and diameter of about 85 mm (Fig. 1). They are used in diesel powered vehicles.

Assembling of gas oil filters is in most cases an automated

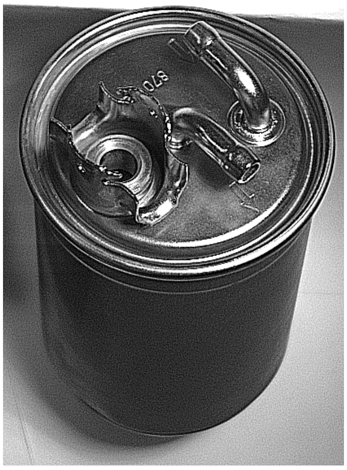


Figure 1: An arbitrary view of a gas oil filter.

process. The assembly line for assembling gas oil filters that has been developed lately was designed to assemble various types of gas oil filters with covers having different appearances (Fig. 2).

Figure 2: Various types of gas oil filters have different appearance.

For instance, input/output hole is or is not present, orientation of filter tubes can differ, the surface color can vary, etc.

For each filter type the assembly line must perform some operations, which are specific for this filter type. To do so, the filter type has to be known and the filter has to be set to proper position. Therefore, the filter positioning and filter cover verification is required. Both procedures are required before a) placing rubber rings to the input/output holes, b) testing the airtightness of the assembled product, c) capping the filter tubes, and d) printing filter type label to its casing. Precise positioning (Fig. 3) is especially important for operations a), b), and c), where for example, even small rotational positioning error can cause the production of defective products (a, c), e.g. filters without rubber ring or filters without caps on input/output tubes, or irregular classification of possibly regularly assembled filters (b). Owing to assembly line construction, operation of filter cover verification has to be reliable, i.e. if improper cover appears on the line it can damage the tools (operations a, b, c), or filters can be marked (operation d) incorrectly. Considering the properties of the

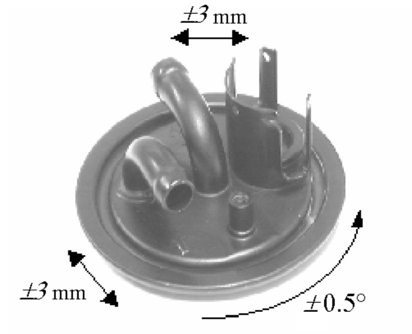


Figure 3: A filter cover and the positioning requirements.

assembly line, the constructors of the production line specified the key objectives for the positioning and type verification system as follows:

- The system must be flexible, with the rotational positioning and part verification capability, without limitation on filter appearance.
- Positioning and part verifications must be performed in the same place.
- Feedback control of positioning is required, such that positioning error can be detected and corrected.
- The system has to be able to operate automatically under the supervision of the assembly line controller.
- Cycle time is limited to 3 s.
- Allowed displacement of filters on the assembly line is ± 3 mm.
- Rotational positioning error must be smaller than $\pm 0.5\,^{\circ}$.

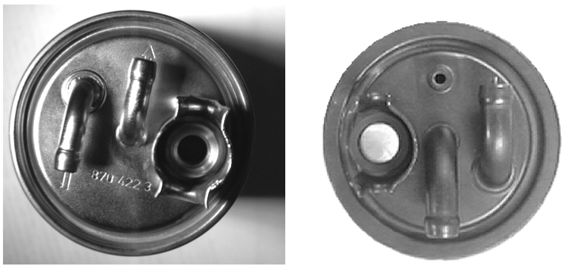
Based on these specifications we have developed a machine vision system that is described in the following sections.

3 Methodology

Considering the main objectives, our goal was to develop a system, which could be easily adapted to any type of gas oil filter. To achieve the goal an appropriate imaging system setup was selected, and adequate machine vision algorithms were employed. This is going to be described in more detail in the following subsections.

3.1 Imaging system setup

Under imaging system setup we mean the arrangement of illumination source and sensing device for capturing images (camera). If we want to determine the position and verify the type of an object, gas oil filter in our case, the object has to be illuminated in such a way that its most significant features, which are used for filter type recognition and its position determination, are clearly visible. Furthermore the camera has to be placed in such a way that it provides satisfactory sensitiveness with respect to the object position changes and filter type recognition.



(a) (b)

Figure 4: Oblique illuminated filter cover a), and front illuminated filter cover b).

Considering the requirements, either front or oblique illumination can be used. Oblique illumination casts shadows of parts that are higher than the cover plate (Fig. 4(a)). Such illumination provides high sensitivity due to rotational changes. This sensitivity reflects mostly the changes of parts that are attached on the top of the cover plate and are higher than the filter cover is. Due to imprecise fastening of those parts, their position with respect to the filter cover plate can vary. Because of those variations filter rotation can not be reliably determined. This can be avoided, if illumination that does not cast any shadows of higher parts to the filter cover plate is selected. Therefore the imaging system with (Fig. 5) ring illumination placed around the camera lens, and camera mounted perpendicular to the filter cover is employed. Such illumination homogeneously illuminates the object, and higher parts do not cast shadows to the cover plate that could be visible to the camera.

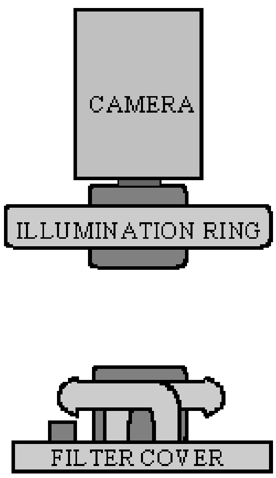


Figure 5: Selected imaging system setup.

Therefore, an in fact 3D object appears as 2D. That allows the determination of filter's rotation and displacement by template matching, based on just one template image (Fig. 4(b)).

3.2 Hardware configuration

The MVS was integrated into an assembly line that was installed in a factory production hall. The industrial hall provides the ambient with normal temperatures and humidity. Such environment allows employment of standard, low cost machine vision hardware. Therefore a PC based MVS, with built-in Matrox Meteor frame grabber and Panasonic CCD camera with standard CCIR video output is utilized. The PC is furthermore equipped with Meilhaus digital I/O card, which provides the communication to the assembly line controller. The positioning is performed by Isel stepper motor, where its controller is commanded by the PC's RS 232 communication port (Fig. 6).

The configuration described allows autonomous positioning of gas oil filters by the MVS, and effective communication of the machine vision system with the assembly line controller.

Autonomous positioning of gas oil filters by the MVS is important for the feedback control. In this case the MVS can autonomously execute operations required to properly position the object. For example when a command for object positioning is received the MVS determines the orientation of the filter, sends the rotation command to the stepper motor controller, waits until the operation of rotation does not stop, and checks the object position again. This might be repeated several times until required position is achieved or the assembly line controller interrupts the operation. All those operations are running completely without assistance of the assembly line controller. This makes communication with the assembly line controller simple.

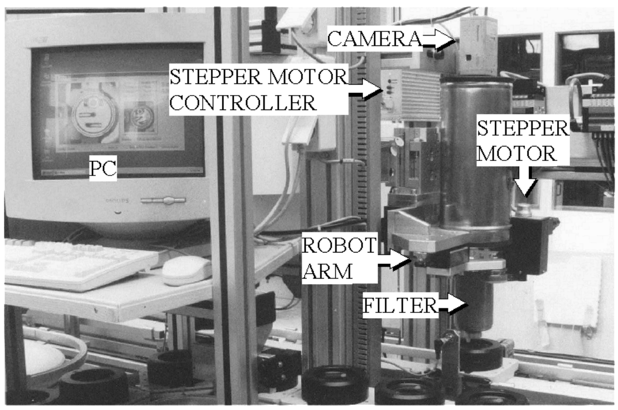


Figure 7: The MVS integrated into the assembly line.

Once the filter, which needs to be positioned and its type determined, is placed below the camera, a specially designed robot arm picks the object, and sets it in front of the camera lens (Fig. 7). Then the assembly line controller sends a filter type data and the start signal, which starts the positioning operation, to the MVS. After the positioning is finished the system sends positioning and type verification results to the assembly line controller and the arm puts the filter back to

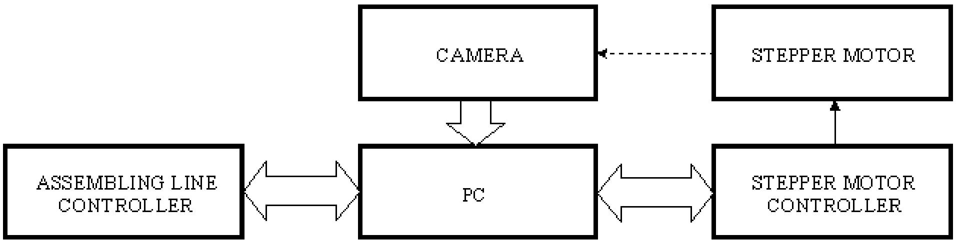


Figure 6: Schematic representation of machine vision system. A closed loop is achieved by visual control.

the conveyor belt. In case that positioning is not successful a false positioning signal is sent to the assembly line controller. This indicates that there is an error on the system positioning device and as a consequence the assembly line stops. The type verification signal informs the assembling controller about the result of filter type verification. If filter type is not verified the assembly line considers particular filter as defective. Such result signals the assembly line to leave the filter on the conveyor belt and to keep it untouched. When the filter is put to the conveyor belt the MVS is prepared to handle the next incoming filter.

3.3 The algorithms

Observing Fig. 4(b) one can see that filter cover is a circular object, with a tiny outer band, which is rotationally invariant, and an inner disk area, that holds all the information about the filter orientation. Therefore, it is advantageous to split the problem into two sub-problems, where smaller regions of the image are analyzed separately. In that case the location of the object must be determined first, and after that the rotation of object can be identified. In addition, the inner region of the cover area holds sufficient information for the filter type verification. The verification can therefore be done by observing just that part of the image.

3.3.1 Location determination The object is located based on a template matching. For that purpose a template image, i.e. the outer band of the filter cover which is rotationally invariant is selected. The region that represents the template is selected manually in the learning phase.

To locate the object the template is shifted with respect to the input image until the best match between template and the image is found. In order to speed up the algorithm a hierarchical approach is employed. It is based on the principle of matching a smaller part of the template (subtemplate), in broader area of the image first. In the areas where the correlation with the subtemplate is higher the whole template is matched to the image to precisely determine the location of the filter in the image. The location where template and the image match best is then selected for rotation determination.

3.3.2 Rotation determination Due to the objective of developing the system which can be easily adapted to different kinds of gas oil filters we decided to employ an appearance based method, based on a principal component analysis (PCA), also known as the Karhunen-Loeve transform as proposed in papers by Murase and Nayar [6], and by Yoshimura and Kanade [7].

Briefly, the appearance based approaches consist of two stages. In the first stage, the learning stage, a set of images (templates) is obtained. The templates are usually highly correlated, and are therefore suitable for compression by PCA [8]. Such templates can be efficiently replaced by a small number of images (“eigenimages”). These eigenimages constitute the so-called “eigenspace”. In the second stage, given an input image, the recognition system projects the image to the eigenspace. The recovered coefficients indicate the particular object class, position, illumination, color, etc.

In our case, the learning phase needs to be done for each filter type separately. This is an off-line process, which consists of the following steps:

- templates at different rotations are acquired,
- each template is normalized, and written as a template vector,
- the template vectors form the template set matrix,
- the covariance matrix of the template set matrix is calculated,
- eigenvalues and eigenvectors of the covariance matrix are computed,
- eigenvectors (eigenimages) that describe the rotation of the object best, are selected to constitute the eigenspace, and finally
- all the template vectors are projected to the eigenspace.

In the procedure of acquiring templates the filter of a given type is rotated in steps for a constant rotation angle ($\triangle\varphi = 1.2°$ in our case) and simultaneously its images are captured. Since the filter can be misplaced its location is found first. Once the location is known, the region in the image that corresponds to the inner disk area of the filter is selected as a template at a given rotation angle. The template is written as a vector, namely the vector $\mathbf{x_i}$, where i is the rotation index ($\varphi = i * \triangle\varphi$). Each template is normalized such that the average intensity of the template is zero and intensity values are within ± 1. Template vectors that describe the filter at different rotations, represent a learning set of templates and constitute the matrix $\mathbf{X}$ of the template image set

$$\mathbf{X} = [\mathbf{x_1}, \mathbf{x_2}, \ldots, \mathbf{x_N}]. \tag{1}$$

Once the templates, which represents all the rotations of the filter are obtained, a covariance matrix $\mathbf{Q}$ of the matrix $\mathbf{X}$ is calculated

$$\mathbf{Q} = \mathbf{X}\mathbf{X}^{\mathbf{T}}. \tag{2}$$

The eigenvectors $\mathbf{e_i}$ and the corresponding eigenvalues $\lambda_\mathbf{i}$ of the covariance matrix $\mathbf{Q}$ are determined by solving the eigenvalue problem. Extraction of the eigenvectors is computationally intensive and is in our case solved by the SVD decomposition algorithm as proposed by Yoshimura [7]. In such a way a number of N-1 highest eigenvalues is acquired. All eigenvectors are needed to represent the templates exactly, while only a small number (k) of eigenvectors is generally sufficient to capture the primary characteristics of the filter at different rotations. A general criterion for selecting the number of eigenvectors that capture important appearance of the image was proposed by Murase et al. [6]

$$T_1 \leq \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{j=1}^{N} \lambda_j}, \tag{3}$$

where T_1 is the threshold, which is close but less than unity. [1] When the eigenvectors ($\acute{\mathbf{e}}_\mathbf{i}$), that constitute the eigenspace are selected, each template is projected to the eigenspace

$$\mathbf{g_i} = [\acute{\mathbf{e}}_\mathbf{1}, \acute{\mathbf{e}}_\mathbf{2}, \ldots, \acute{\mathbf{e}}_\mathbf{k}]^T(\mathbf{x_i}). \tag{4}$$

By projecting all learning samples to the eigenspace, a set of discrete points in the eigenspace is obtained. If we assume that the points are varying smoothly with the rotation changes the position of points can be determined for any rotation. For that purpose a cubic spline interpolation algorithm was used.

Once the projections of templates to the eigenspace are known, the rotation of a filter at an unknown position can be identified as follows:

- the location of filter in the image is determined,
- the inner disk region of the filter in the image is selected as the image of the filter at unknown rotation ($\mathbf{y}$),
- the image of the filter at unknown orientation is normalized,
- normalized image is projected to the eigenspace by the equation
$$\mathbf{z} = [\acute{\mathbf{e}}_\mathbf{1}, \acute{\mathbf{e}}_\mathbf{2}, \ldots, \acute{\mathbf{e}}_\mathbf{k}]^T\mathbf{y}. \tag{5}$$
- the rotation (p) for which the distance (d) between parameters of the templates ($\mathbf{g}$) and projected image of the filter at an unknown rotation ($\mathbf{z}$) is smallest is selected
$$d^p = min\|\mathbf{z} - \mathbf{g}^\mathbf{P}(\varphi)\|. \tag{6}$$

[1]However, such selection of the eigenvectors is optimal when templates have to be reconstructed, while when the rotation of the 2D objects have to be determined other criteria of eigenvectors selection might be more appropriate.

If eigenvectors that constitute the eigenspace are selected. as proposed by Murase et al., the type verification process is simply part of rotation determination. In that case, the minimum distance indicates similarity between the template that matches best and the image of the filter. If the distance is higher than a predefined value, the observed filter is considered as a correct one.

3.4 Software implementation

The GUI software was written for the Microsoft Windows NT operating system. The code was developed by Borland's C++ Builder. The software provides communication between the PC and the assembly line controller, and additionally guides the stepper motor controller. The application can run in three different modes, e.g. automatic, manual and learning mode. Most of the time, the software is expected to

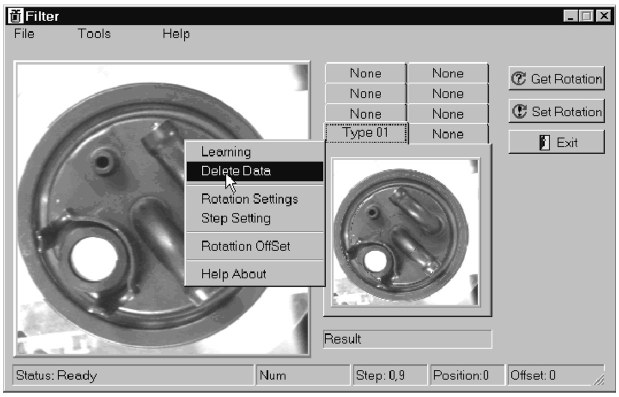


Figure 8: Main window of the application in the manual mode of operation.

run in automatic mode. In this mode the application communicates with the assembly line controller. It reads the input data and executes the controller's commands, while a desktop user can simply monitor how the system is performing and switch the system to the manual or learning mode. In the manual mode (Fig. 8) the system enables a user to test the performance, e.g. determine the filter rotation, set the filter to a preferred position and verify the filter type. Learning mode of the system is provided for adjusting the system for a new filter type.

4 Experimental results

The implemented system is capable to autonomously operate, by communication with the assembly line controller. Tests obtained from a set of nearly 1000 sequentially assembled products, with regular filter covers, confirm that the system works reliably. The filter positioning error is smaller than $\pm 0.3°$. Such positioning is usually achieved in the first attempt. If positioning is not successful in the first time, than the orientation of the filter after the first attempt is close to correct result, i.e. positioning error is within $\pm 1°$. The second manipulation sets the filter within error limits, i.e. $\pm 0.3°$. During the test experiment the system did not do any wrong manipulation. The filter type verification test proved that system is able to distinguish various types of filters and to perceive damaged filter covers. The time of the complete operation is less than 0.9 second on a Pentium 166MHz PC. This time includes position determination and filter positioning. Time of position determination is less than 0.4 second, and depends on number of eigenimages employed, while the time of positioning is up to 0.5 second and depends on rotation angle required.

5 Conclusions

The paper has presented the industrial MVS that verifies and rotates various types of gas oil filters. The MVS is based on template matching and appearance based approach. The results confirm that appearance based methods are suitable for implementation in MVS. Simple procedure of learning about new objects having different appearances allows that even unskilled users can learn to handle with the MVS in a short time. The system is integrated into the assembly line where it can efficiently verify and position up to eight different types of gas oil filters simultaneously, and sets them to a preferred orientation. The described systen can be easily adapted for rotational positioning of different types of objects.

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