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# Real-time in-plane rotation estimation of pharmaceutical tablets: a feature based approach

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## Abstract

*Visual quality inspection plays an important rule in quality control. With visual inspection it is ensured that the inspected surface meets the requirements; that the surface is free of irregularities, such as cracks, dents, and scratches. Detection of irregularities can, however, be a challenging task, especially on complex surfaces, where it is necessary to differentiate between surface irregularities and expected surface variations. Differentiation is done by comparing a sample with a reference model, which requires an accurate spatial alignment between the two. In this paper we focus on visual quality inspection of pharmaceutical tablets. While inspected, tablets are mechanically constrained, thus alignment simplifies to in-plane rotation estimation. For in-plane rotation estimation we propose a method using histograms of oriented gradients (HOG) and a nearest-neighbor regression in HOG feature space. Method was evaluated on four datasets of pharmaceutical tablets, varying in size, shape and color. The results show that the proposed method is superior in robustness, with comparable accuracy to the methods previously used for rotation estimation of pharmaceutical tablets.*

## 1 Introduction

All pharmaceutical tablets must be uniquely marked, to enable unique identification and to avoid hazardous mix-ups. Due to imperfect production process a compliant visual appearance is ensured by visual inspection [1], [2]. Visual inspection of pharmaceutical tablets is a difficult task, especially of tablets with complex geometries, because it is necessary to differentiate between defects and expected surface variations. Differentiation is done by comparing a sample with an ideal reference model which, however, requires an accurate spatial alignment between the two.

In this paper, we address the spatial alignment of pharmaceutical tablets for visual quality inspection of pharmaceutical tablets [1]. While inspected, tablets are mechanically constrained. This simplifies the alignment to in-plane rotation estimation (Fig. 2). Nevertheless, rotation estimation of pharmaceutical tablets is a challenging task, because tablets vary in shape, color, texture, and because of high speed requirements. The task is additionally challenging because of normal intra-tablet variability which is a result of imperfect production process.

Špiclin et. al [3] proposed the following three registration methods for in-plane tablet rotation estimation: Direct Pixel Matching (DPM), Principal Axes Matching (PAM), and Circular Profile Matching (CPM). The first method (DPM) evaluates the normalized cross-correlation of a sample image and the rotating reference image. A rotation angle is determined by the maximum value of the normalized cross-correlation. By contrast, circular profile matching is based on extraction and alignment of circular profiles. Circular profiles are obtained by the radial integration ($I(\phi) = \int_{r_1}^{r_2} I(-r\sin\phi, r\cos\phi)\,dr$) within a ring centered at the tablet center. By integration the 2D image $I(x, y)$ is reduced to 1D profile $I(\phi)$ – the angle is estimated by 1-D cross correlation of reference and sample circular profile: $I_r(\phi) * I_s(\phi)$. PAM as the third method estimates the angle by matching principal axes of the reference and a sample object [4]; method is suitable only for objects with distinctive assimetric structures. Morever, this approach requires additional verification step, due to residual $\pm\pi$ sign ambiguity.

Described methods used for rotation estimation are rather basic, because of speed requirements ($< 5$ ms per estimation). Methods work sufficiently well only if center estimations are accurate (DPM, CPM) or for objects with distinctive shape asymmetry (PAM). Furthermore, due to global similarity measure (i.e. cross-correlation), methods are affected by large irregularities that distort the tablet appearance – leading to inaccurate spatial alignment. An inaccurate spatial alignement further leads to erroneous inspection results, and finally to lost profits.

In order to increase position invariance and alignment robustness, we propose a feature based approach to in-plane tablet alignment.

Figure 1. Mechanically constrained inspected products on a rotating drum.

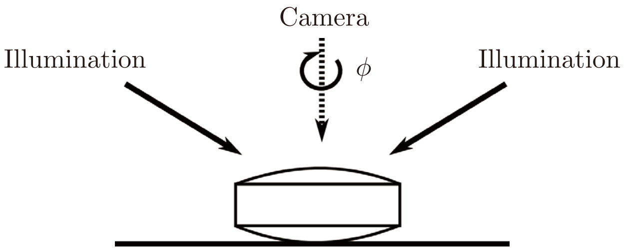


Figure 2. Illumination and camera setup. Camera view is parallel to the tablet rotation axis

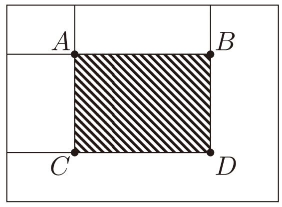


Figure 4. The value $I(x, y)$ at any point $(x, y)$ is the sum of all the pixels above and to the left of $(x, y)$ inclusive, $I(x, y) = \sum_0^x \sum_0^y i(x', y')$ - integral of pixel values within arbitrary rectangle $ABCD$ is obtained by $I(D)+I(A)-I(B)-I(C)$.

## 2 Rotation estimation

Prior to alignment, all the tablets are segmented using method proposed by Možina et. al [5], by which an object center and an object's bounding window are obtained. Rotation is estimated with a nearest-neighbour search in HOG feature space. A rotation angle $\phi$ (Fig. 2) for each sample image $I_s$ is estimated by mapping the sample image to HOG feature space then searching for a nearest neighbour in the reference set $T(\phi)$. The reference set contains HOG feature representations for reference object at different angles, and is constructed by rotating the reference image $I_r$ by $\phi$; we assume a similar object appearance, regardless of the rotation angle.

The method is described in three steps. First, we briefly describe Histograms of Oriented Gradients, second we describe a procedure for reference set construction, and finally we describe the rotation estimation.

### 2.1 Histograms of Oriented Gradients

Dalal and Triggs [6] proposed Histograms of Oriented Gradients, to answer the question of feature sets for robust visual object recognition. Histograms of Oriented Gradients feature set is obtained from a grid of spatial cells; each spatial cell contains a $k$-bin weighted (with absolute gradient) histogram of vector orientations. Spatial cells are concatenated into larger blocks of $N \times M$ cells and normalized to a $L_1$ ($\sum_i |x_i| = 1$) or a $L_2$ ($\sqrt{\sum_i x_i^2} = 1$) unit length. Finally, vectors over all blocks are merged to a HOG feature vector (Fig. 3). Subsequently, Zhu et. al [7] proposed an integral image (Fig. 4) approach to HOG calculation. This approach enables a constant time calculation of histograms of oriented gradients over arbitrary rectangular regions. For integral image based HOG calculation, a separate integral image is stored for each histogram bin. First, an image $I_b$ is initialized for each histogram's bin, then a gradient orientation at each image's pixel is bilinearly interpolated; results are stored in the corresponding image. Lastly, an integral image for each histogram bin is calculated from each image $I_b$. Value for each element of HOG vector is independently calculated from the corresponding integral image – calculation of HOG vector thus requires $4 \times k$ access operations.

### 2.2 Reference set construction

A reference set is built from a single reference image $I_\phi$ rotated in $r$ degree steps around the rotation axis. Step size $r$ is user determined and determines the theoretical upper bound of rotation estimation accuracy. Next, each rotated image $I_\phi$ is transformed to a HOG feature space $I_\phi \to \boldsymbol{\tau}_\phi$. As a result of mapping images $I_\phi, \phi = [0, \ldots, 2\pi]$ to HOG feature space $\boldsymbol{\tau}_\phi$ we obtain a reference set $\mathbf{T}(\phi)$.

HOG features are calculated over a deterministically constructed multi-scale set of cells $W$; each scale in a set determines the size of cells that uniformly tile the window. By iteratively proceeding from largest to the smallest scale, cell size is reduced by $2\times$ between two neighbouring scales, - forming a multi-scale set of candidate cells.

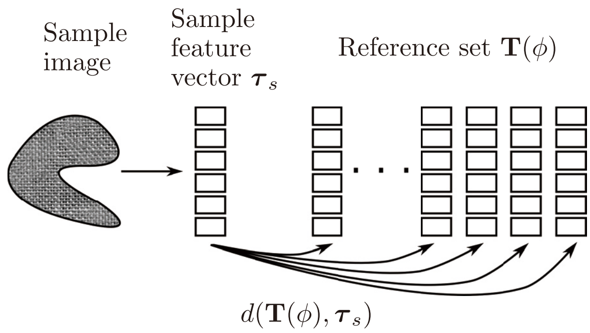


Figure 5. Rotation angle is estimated by a nearest neighbour search in feature space.

### 2.3 Rotation estimation

With a reference set $\mathbf{T}(\phi)$, a rotation angle for each sample image $I_s$ is estimated as follows: first, a sample image is mapped to a HOG feature space $I_s \to \boldsymbol{\tau}_s$, with features calculated over all the cells $w \in W$. A rotation angle is then estimated (Fig. 5) by finding the nearest neighbour in reference set $\mathbf{T}(\phi)$:

$$\phi_{estimate} = \arg\min_\phi d(\mathbf{T}(\phi), \boldsymbol{\tau}_s) \quad (1)$$

where $d(\mathbf{T}(\phi), \boldsymbol{\tau}_s)$ is an Euclidean distance between feature vectors $\boldsymbol{\tau}_s$ and $\mathbf{T}(\phi)$.

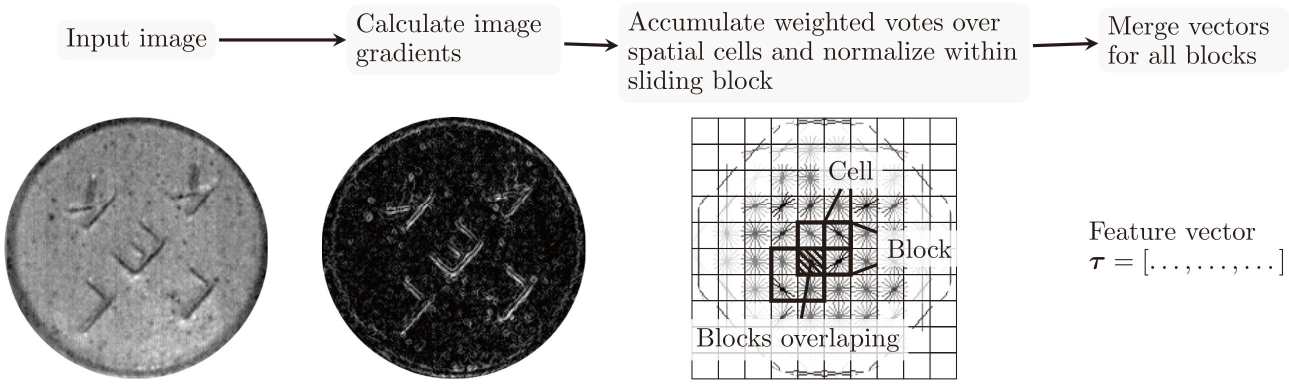


Figure 3. Histograms of Oriented gradients.

### 2.3.1 Implementation details

Method was implemented in C++ and compiled with Visual Studio. The same parameters were used for all the datasets. Three scales were used to construct a multi-scale cell set; half object size at start then decimating cell size by $2\times$ with each increasing scale. A 9-bin histogram was calculated for each separate cell, which was merged to a $2 \times 2$ block of cells and normalized to $L_1$-norm. The reference set was constructed with a 1 degree step. For nearest-neighbour search, we used an exhaustive search. Use of a space-partitioning data structure (e.g. kd-tree [8]) was not feasible, due to high dimensionality of a HOG feature vector.

## 3 Experiments and results

The proposed method, denoted as HBM, was evaluated on four datasets provided by Špiclin [3]. Evaluation datasets were captured with a trilinear line-scan camera and a fixed illumination on a Sensum SPINE inspection system (Sensum). An illumination and camera setup is shown in Fig. 2. Datasets contain 514, 219, 212, and 183 images of tablets RTD73, ELP20, 500, and LEK respectively, differing in size, color, and shape (Fig. 6).

To allow objective comparison of the proposed method, we evaluated registration robustness and accuracy by evaluation criteria proposed by Špiclin et. al [3]. The robustness of the method was estimated by the percentage of successful registrations (Hits); successful is a registration with absolute angular error less than 5°. Registration accuracy was measured by the mean absolute angular error (Eq. 3).

An absolute angular error $\epsilon$ is the difference between reference angle $\phi_{ref}$ and an estimated angle $\phi_{estimate}$:

$$\epsilon = |\phi_{ref} - \phi_{estimate}|. \tag{2}$$

A reference angle $\phi_{ref}$ is obtained with 5 manually positioned corresponding points $\{x_i^r, y_i^r\}$ on reference and points $\{x_i^s, y_i^s\}$ on sample image. Angle is obtained by minimizing the mean square distance between corresponding points as a function of angle $\phi_{ref}$:

$$\begin{aligned}
\begin{bmatrix} x_i^r \\ y_i^r \end{bmatrix} &= \begin{bmatrix} \cos\phi_{ref} & \sin\phi_{ref} \\ -\sin\phi_{ref} & \cos\phi_{ref} \end{bmatrix} \begin{bmatrix} x_i^s \\ y_i^s \end{bmatrix} \\
\varepsilon &= \sum_{i=1}^{5} (x_i^r - x_i^s \cos\phi_{ref} - y_i s \sin\phi_{ref})^2 + \\
&\quad \sum_{i=1}^{5} (y_i^r - x_i^s \sin\phi_{ref} - y_i^s \cos\phi_{ref})^2 \\
\frac{\partial\varepsilon}{\partial\phi_{ref}} &= \cos\phi_{ref} \sum_{i=1}^{5} (x_i^s y_i^r - x_i^r y_i^s) + \\
&\quad \sin\phi_{ref} \sum_{i=1}^{5} (x_i^r x_i^s + y_i^r y_i^s) = 0 \\
\phi_{ref} &= \arctan \frac{\sum_{i=1}^{5} (x_i^s y_i^r - x_i^r y_i^s)}{\sum_{i=1}^{5} (x_i^r x_i^s + y_i^r y_i^s)}
\end{aligned} \tag{3}$$

Results for all the methods are presented in Table 1. In addition, Fig. 7 shows a cumulative sum of successful registrations with respect to maximum absolute angular error.

(a) (b) (c) (d)

Figure 6. Evaluation datasets. The 500 dataset contains 212 images of oblong tables (c). Datasets RTD75 (b), ELP20 (c), and LEK (d) contain 514, 219, and 183 images of round tablets respectively.

## 4 Discusion

Method was evaluated on four different datasets of pharmaceutical tablets. Registration of pharmaceutical tablets is a challenging task, because tablets are produced in various shapes, sizes, colors, and with various imprints. Further registration complexity arises

Table 1. Registration results for HOG based rotation estimation and the three reference registration methods

| | RTD75 | ELP20 | 500 | LEK |
|---|---|---|---|---|
| **Error** (°) | | | | |
| DPM | 1.17 | 1.17 | 1.58 | 0.86 |
| PAM | 2.44 | 2.71 | 0.80 | 2.31 |
| CPM | 0.72 | 0.54 | 0.83 | 0.75 |
| HBM | 0.60 | 0.74 | 0.57 | 1.27 |
| **Hits** (%) | | | | |
| DPM | 100 | 100 | 94.3 | 99.5 |
| PAM | 56.0 | 21.5 | 86.8 | 44.3 |
| CPM | 100 | 100 | 100 | 99.5 |
| HBM | 100 | 100 | 100 | 100 |
| **Time** (ms) | | | | |
| DPM | 109 | 184 | 227 | 191 |
| PAM | 1.01 | 1.42 | 1.66 | 1.46 |
| CPM | 3.18 | 3.49 | 3.01 | 3.15 |
| HBM | 1.52 | 1.56 | 1.53 | 1.57 |

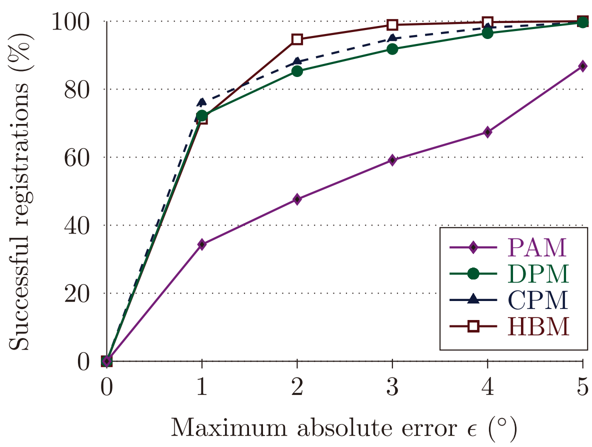


Figure 7. Cumulative percentage of successful registrations as a function of maximum absolute registration error.

from imperfect illumination and mechanical manipulation, and various surface irregularities. Evaluated method was compared with three methods described by Špiclin et. al [3]. Registration speed was recorded, however, the running times cannot be directly compared, as the methods were executed on different computers. Nevertheless, we can still infer that the proposed method is a feasible option for real-time rotation estimation. The percentage of successful registrations for the proposed method is higher than for compared methods. The DPM method is directly affected by the outliers caused by product's defects and by irregular illumination. By contrast CPM integrates values over the tablet radius, thus increasing robustness, and performance, but decreasing discriminative power. This is particulary pronounced with near symmetric imprints. The PAM method simplifies rotation estimaton by matching the principal axes, but is useful only for objects with distinctive asymmetric structures, and has a residual $\pm\pi$ sign ambiguity. Accuracy, evaluated only for successful registrations, had an upper bound at 5°. The accuracy of the proposed method is comparable with the accuracy of CPM and DPM while accuracy of PAM is considerably worse. All the methods, other than PAM, are theoretically bounded by the sampling resolution.

## 5 Conclusion

In this paper we propose a registration method for in-plane rotation estimation of pharmaceutical tablets. A feature based registration is performed, by constructing a reference feature set of rotated reference images in mapped feature space. A rotation angle of a sample is then estimated by finding its nearest-neighbour in that reference set.

Method was evaluated and compared on four datasets of pharmaceutical tablets. The results show that the proposed method is a feasible option for rotation estimation in industrial environments. Although the evaluation was made on datasets of pharmaceutical tablets, we consider the method useful for rotation estimation of arbitrary objects.

## References


[1] M. Bukovec, Ž. Špiclin, F. Pernuš, and B. Likar, "Automated visual inspection of imprinted pharmaceutical tablets," *Measurement Science and Technology*, vol. 18, pp. 2921–2930, Sept. 2007.

[2] M. Možina, D. Tomaževič, F. Pernuš, and B. Likar, "Automated visual inspection of imprint quality of pharmaceutical tablets," *Machine Vision and Applications*, vol. 24, pp. 63–73, 2013.

[3] Ž. Špiclin, M. Bukovec, F. Pernuš, and B. Likar, "Image registration for visual inspection of imprinted pharmaceutical tablets," *Machine Vision and Applications*, vol. 22, pp. 197–206, Jan. 2011.

[4] N. M. Alpert, J. F. Bradshaw, D. Kennedy, and J. A. Correia, "The principal axes transformation–a method for image registration," *J Nucl Med*, vol. 31, pp. 1717–1722, Oct. 1990.

[5] M. Možina, D. Tomaževič, F. Pernuš, and B. Likar, "Real-time image segmentation for visual inspection of pharmaceutical tablets," *Machine Vision and Applications*, vol. 22, pp. 145–156, 2011.

[6] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, vol. 1, pp. 886 –893 vol. 1, june 2005.

[7] Q. Zhu, M.-C. Yeh, K.-T. Cheng, and S. Avidan, "Fast human detection using a cascade of histograms of oriented gradients," in *Proceedings of the 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Volume 2*, CVPR '06, (Washington, DC, USA), pp. 1491–1498, IEEE Computer Society, 2006.

[8] J. L. Bentley, "Multidimensional binary search trees used for associative searching," *Commun. ACM*, vol. 18, pp. 509–517, Sept. 1975.