Invariant Classification of Red Blood Cells

A Comparison of Different Approaches

Daniel Keysers, Jörg Dahmen, and Hermann Ney

Lehrstuhl für Informatik VI, Computer Science Department
RWTH Aachen — University of Technology, D-52056 Aachen, Germany
Email: {keysers, dahmen, ney}@informatik.rwth-aachen.de

Abstract. In this paper we evaluate the performance with respect to classification of red blood cells of an invariant statistical classifier that was successfully applied to a variety of object recognition tasks. The classifier is based on distance functions invariant to affine transformations and additive brightness and on kernel densities within a Bayesian framework. Given a database of 5062 grayscale images, we follow an 'appearance based' approach obtaining an error rate of 16.3%, lying below the human error rate of greater than 20%. Our experiments show the general applicability of the approach taken. A comparison with results obtained in other domains underlines the task dependency of the performance of different classification algorithms.

1 Introduction

In medical tests, the effect of a drug on the cell membrane of red blood cells (RBC) may be of interest, possibly measured by the induced shape changes [1]. The comparison of the shape changes with known behavior in presence of drugs for evaluation is usually performed by a human expert and therefore time consuming and costly. This fact and the desire for reproducible results stress the need for automatic classification. We present an invariant statistical approach to classifying RBC automatically. The experience with classification tasks such as radiograph categorization and optical character recognition suggests that invariance plays a major role for object recognition [2]. Since the images of RBC used in this work are taken during sedimentation, one observes high variability here, indicating the usage of *invariant classification methods.* We evaluate the performance of a Bayesian classifier based on kernel densities, tangent distance and virtual data creation, which has obtained excellent results in the domains mentioned above. Furthermore we compare it to a different method based on invariant features presented recently in [3]. Thus the purpose of this work is twofold – to give evidence for the general applicability of the approach presented here and to introduce a new method to the automatic classification of RBC.

The experiments are conducted on a set of 5062 images (which were labelled as *stomatocyte* (3259), *echinocyte* (916) resp. *discocyte* (887) by an expert), where each cell is represented by a 64×64 pixels sized grayscale image. Invariance is incorporated using invariant Gaussian densities based on tangent distance (TD), which compensates for small affine transformations and additive brightness changes. We obtain an error rate of 16.3% using the proposed classifier, which seems high for a three class problem but is still considerably lower than

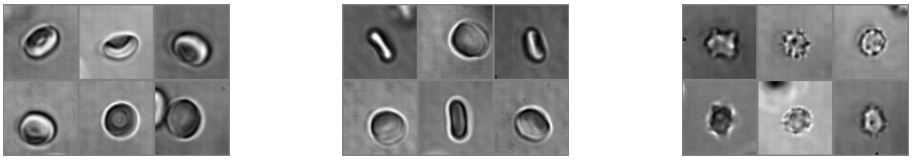

Fig. 1. RBC example images, left to right: stomatocytes, discocytes, echinocytes.

the human error rate of >20% [4]. Yet the error rate is higher than that of a statistical classifier using Gaussian mixture densities (GMD) and rotation-, scale- and translation-invariant (RST) features based on the Fourier-Mellin transform, which obtained an error rate of 15.3% [3]. On the other hand for the task of optical character recognition (OCR) the classifier presented here performs considerably better than the approach based on invariant features (2.2% error on the US Postal Service database [2]). This comparison shows that the choice of the appropriate classifier strongly depends on the specific task within the domain of object recognition. Nevertheless it can be observed that the presented classifier performs well in a variety of object recognition tasks (OCR, radiograph classification [2], RBC classification), yielding state-of-the-art results.

2 RBC classification and invariance

The images are taken in a capillary where the RBC show their shapes without applied forces during sedimentation [5]. Figure 1 shows some example images. With only 5062 images available, we do not subdivide the dataset into a training and a test set, but make use of a *leaving-one-out approach*. I.e., when classifying an image we use the remaining 5061 images as training data, still strictly separating training and test data, but fully using all available information. In [3], ten-fold cross-validation was used instead, due to the larger training requirements of a GMD based classifier using linear discriminant analysis (LDA).

One drawback of the RBC database is that there is only one result obtained by a competing classification method available. Therefore, and because we wish to compare the results obtained on the RBC data with those on other databases, we also briefly present results for the US Postal Service database. For the performance of the classifier on a database of radiographs see e.g. [6]. The USPS database contains 7291 training and 2007 test samples of isolated, handwritten digits, which are represented by 16×16 pixels sized grayscale image. It is known to be a hard task in the domain of OCR with a human error rate of 2.5% [7].

We apply *appearance based* pattern recognition, i.e. we interpret each pixel of an image as a feature, which is a contrary approach to the extraction of invariant features as employed in [3]. The classifier used is a kernel density based classifier, where additional emphasis is put on invariance with respect to relevant transformations, as explained briefly in the following. (For more detailed information see e.g. [2].) There exists a variety of ways to deal with the problem of invariance in pattern recognition, where one is the use of invariant distance measures within a statistical classifier, which replaces the commonly used Euclidean or the Mahalanobis distance. In the following, we sketch the idea of one such distance measure called *tangent distance*, which proved to be especially effective

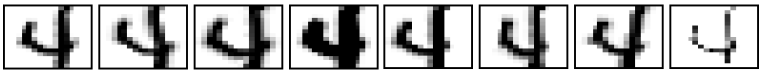

Fig. 2. Examples for tangent approximation (affine transformations and line thickness)

in the domain of digit recognition and was introduced by SIMARD et al. (see e.g. [7]). When an image $x \in \mathbb{R}^D$ is transformed (e.g. scaled and rotated), the set of all transformed patterns is a manifold in pattern space. The distance between two patterns can now be defined as the minimum distance between their respective manifolds, truly invariant with respect to the regarded transformations. As computation of this distance is a hard non-linear optimization problem, small transformations of the pattern x are approximated by a tangent subspace to the manifold at the point x. This subspace is obtained by adding to x a linear combination of the vectors $x_l,\ l = 1, \dots, L$ called *tangent vectors* that span the tangent subspace. We obtain a first-order approximation of the manifold which is the subspace containing all $x_\alpha = x + \sum_l \alpha_l x_l$ for $\alpha \in \mathbb{R}^L$. The (squared) single-sided TD with tangents in x is then defined as

$$d(x, \mu) = \min_\alpha \left\{ ||x + \sum\nolimits_l \alpha_l x_l - \mu||^2 \right\}$$

and can be computed efficiently as it is a linear least squares optimization problem. Example images that were computed using the tangent approximation to the manifold are shown in Fig. 2 (with the original image on the left; here, an image from the USPS corpus is chosen to illustrate the effect). Similarly, we can define a double-sided TD approximating both manifolds. TD can lead to transformation tolerance in classification and can furthermore be easily incorporated into statistical classifiers as it has a well-founded probabilistic interpretation [8].

By adding to the training set a number of transformed instances of the original data (*virtual data*), one can achieve better performance of the classifier without actually requiring more training data. For the RBC task we used rotations by multiples of $\pi/2$ and flipping. For the OCR data, rotation and flipping is not desired, but small image shifts were chosen. It is also possible to use virtual data for testing, which can improve classification significantly [9].

3 Results and comparison of approaches

Table 1 shows a summary of the obtained results in comparison to the GMD approach with RST-invariant features presented in [3]. We started our experiments regarding the appearance based method with a nearest neighbor (1-NN) classifier, which is often used as a baseline result. We found that applying a two-bin histogram equalization to the data during classification improved the result

Table 1. Summary of Results for the RBC data

Method		ER [%]
Human [4]		>20.0
GMD [3]	appearance based	31.0
	RST-invariant	18.8
	+ LDA	15.3

This work:	1-NN	24.4
	+ histogram equal.	21.4
	+ kernel densities	19.6
	+ tangent distance	17.8
	+ virtual data	16.3

from 24.4% to 21.4%, diminishing different background graylevel intensities in the data. By using a kernel density based Bayesian classifier the error rate could be further reduced to 19.6%. Finally, we added two ingredients to improve transformation tolerance, i.e. tangent distance and virtual data as introduced above. These led to the best error rate for the appearance based approach of 16.3% error. The tangents used in these experiments were six for the affine transformations and one for additive brightness offsets. By using a simple *reject* rule (reject, if the negative log-likelihood of the second best class is not at least r% larger than that of the best class) we could reduce the error rate to 15.5% at 1.4% reject for $r = 10$ resp. to 14.5% at 3.9% reject for $r = 12$. This is slightly inferior to the result of 13.6% error at 2.4% reject as reported in [3]. We also performed a number of further experiments, which did not lead to improved recognition rates. Among these was the use of image normalization w.r.t. rotation, the use of gradient information as additional features and the application of the invariant distance measure called *image distortion model*, where the latter led to significant improvements in the case of radiograph categorization [2].

The main motivation for the experiments presented here was that the appearance based classification approach with invariance methods (tangent distance, image distortion model, virtual data) achieved excellent results on other tasks. A summary of results for the USPS task with many research results from competing methods available is given in Table 2. Likewise for the IRMA (Image Retrieval in Medical Applications) database of radiographs, the approach performed very well, although only few other results are known. For detailed information on the IRMA categorization and the performance of the algorithm see e.g. [6].

The obtained results show that on this specific task – RBC classification – the appearance based approach does not lead to the best possible performance, while it does for some OCR tasks. This observation can be explained by regarding the different types of variability present in the data: the RBC images appear in rotations of all possible angles during sedimentation, while handwritten digits are only subject to small rotations and some other transformations with comparatively small extent. Thus, the information loss inherent in the extraction of invariant features is tolerable for RBC images but not for images of digits, while tangent distance is able to model small transformations in OCR, but does not perform as well for larger transformations. Nevertheless it can be observed that the usage of tangent distance and virtual data improves classification significantly. The presented method has the advantage that less parameters need to be chosen, suggesting better generalization properties.

Table 2. Summary of results for USPS
*: obtained with a training set extended by 2,400 machine-printed digits

Method		ER [%]
1-NN Classifier [2]		5.6
GMD	appearance based [9]	6.0
	LDA, virtual data [9]	3.4
TD	1-NN [2]	3.3
	KD, virtual data [2]	2.2

Method	ER [%]
Human Performance [7]	2.5
Neural Net (LeNet1/4) [7]	4.2
Support Vectors [10]	3.0
Boosting [7]	*2.6
Tangent Distance [7]	*2.5

4 Conclusion

In this paper we evaluated the applicability of an invariant statistical classification approach to a medical task. The proposed methods – which achieve high performance on other data – yield a competitive result on this task of RBC classification without tedious adaptation. This suggests the general usefulness of the approach for a wide range of applications in the field of object recognition. Yet, we could not improve the previously presented result based on extraction of invariant features, for which we gave some explanation. It seems likely that a combination of these two approaches may lead to better recognition, which remains to be examined in the future. Furthermore, the choice of an appropriate classifier seems to depend on the specific object recognition task.

Acknowledgement

The authors wish to thank the Department of Physiology, RWTH Aachen, especially Mr. Jens Hektor for his support and Mrs. H. Horstkott and Mrs. R. Degenhardt for manually classifying the RBC images used in our experiments.

References

1. B. Deuticke, R. Grebe, and C. Haest. Action of Drugs on the Erythrocyte Membrane. In J. Harris, editor, *Blood Cell Biochemistry*, volume 1. Plenum Press, New York, pages 475–529, 1990.
2. D. Keysers, J. Dahmen, T. Theiner, and H. Ney. Experiments with an Extended Tangent Distance. In *Proceedings 15th International Conference on Pattern Recognition*, volume 2, Barcelona, Spain, pages 38–42, September 2000.
3. J. Dahmen, J. Hektor, R. Perrey, and H. Ney. Automatic Classification of Red Blood Cells using Gaussian Mixture Densities. In *Bildverarbeitung für die Medizin*, München, pages 331–335, March 2000.
4. T. Fischer. Department of Physiology, RWTH Aachen University of Technology, personal communication, 1999.
5. M. Schönfeld and R. Grebe. Automatic Shape Quantification of Freely Suspended Red Blood Cells by Isodensity Contour Tracing and Tangent Counting. *Computer Methods and Programs in Biomedicine*, 28:217–224, 1989.
6. J. Dahmen, D. Keysers, M. Motter, H. Ney, T. Lehmann, and B. Wein. An Automatic Approach to Invariant Radiograph Classification. In *Bildverarbeitung für die Medizin*, Springer, Lübeck, Germany, March 2001. This volume.
7. P. Simard, Y. Le Cun, J. Denker, and B. Victorri. Transformation Invariance in Pattern Recognition — Tangent Distance and Tangent Propagation. In G. Orr and K.-R. Müller, editors, *Neural networks: tricks of the trade*, volume 1524 of *Lecture Notes in Computer Science*, Springer, Heidelberg, pages 239–274, 1998.
8. D. Keysers, J. Dahmen, and H. Ney. A Probabilistic View on Tangent Distance. In *22. DAGM Symposium Mustererkennung 2000*, Springer, Kiel, Germany, pages 107–114, September 2000.
9. J. Dahmen, D. Keysers, M. O. Güld, and H. Ney. Invariant Image Object Recognition using Mixture Densities. In *Proceedings 15th International Conference on Pattern Recognition*, volume 2, Barcelona, Spain, pages 614–617, September 2000.
10. B. Schölkopf, P. Simard, A. Smola, and V. Vapnik. Prior Knowledge in Support Vector Kernels. In M. I. Jordan, M. J. Kearns, and S. A. Solla, editors, *Advances in Neural Inf. Proc. Systems*, volume 10. MIT Press, pages 640–646, 1998.