Hyperspectral Detection of Citrus Damage with a Mahalanobis Kernel Classifier

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Abstract

This letter presents a full computer vision system for the identification of postharvest damages in citrus packing houses. The method is based on the combined use of hyperspectral images and the Mahalanobis kernel classifier. More accurate and reliable results compared to other methods are obtained in several scenarios and acquired images.

1 Introduction

Early fungi infection detection is especially important in citrus packing houses since a few infected fruits can spread the infection to a whole batch, causing great economic losses and affecting further operations, such as storage or exportation. *Penicillium digitatum sp* produces the most important postharvest damages in citrus packing houses. Nowadays, the detection of rotten fruit in the citrus packing lines is carried out visually under ultraviolet illumination, and fruits are removed manually. This procedure, however, may be harmful for operators and operationally inefficient.

In this context, the introduction of hyperspectral sensor imaging permits the analysis of an image at different wavelengths, and the resulting spectral signature (or *spectrum*) can be used to identify a given defect. Very few works are available concerning the detection of citrus damages using machine learning techniques [1, 2, 3]. The high number of acquired channels is beneficial for detection but also poses the problem of the curse of dimensionality for many of the classifiers used so far. In such situations, SVMs have revealed very efficient [4]. In this paper, we propose the use of support vector machines (SVM) with the Mahalanobis kernel to classify images of citrus with fungal damages. This kernel handles the different intrinsic relevance of spectral channels more efficiently, as their relative importance is learned from the data.

2 Mahalanobis kernel for SVM classifiers

Given a labeled training data set $\{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_n, y_n)\}$, where $\mathbf{x}_i \in \mathbb{R}^N$ and $y_i \in \{-1, +1\}$, and a nonlinear mapping $\boldsymbol{\phi}(\cdot)$, usually to a higher (possibly infinite) dimensional Hilbert space, $\boldsymbol{\phi} : \mathbb{R}^N \longrightarrow \mathcal{H}$, the SVM method solves:

$$\min_{\mathbf{w},\xi_i,b} \left\{ \frac{1}{2}\|\mathbf{w}\|^2 + C \sum_i \xi_i \right\} \tag{1}$$

constrained to:

$$y_i(\langle \boldsymbol{\phi}(\mathbf{x}_i), \mathbf{w}\rangle + b) \geq 1 - \xi_i \qquad \forall i = 1, \ldots, n \tag{2}$$

$$\xi_i \geq 0 \qquad \forall i = 1, \ldots, n \tag{3}$$

where $\mathbf{w}$ and b define a linear classifier in the feature space. The non-linear mapping function $\boldsymbol{\phi}$ is performed in accordance with Cover's theorem [5], which guarantees that the transformed samples are more likely to be linearly separable in the resulting feature space. The regularisation parameter C controls the generalisation capabilities of the classifier and it must be selected by the user, and ξ_i are positive slack variables enabling to deal with permitted errors.

It is worth noting that all $\boldsymbol{\phi}$ mappings used in the SVM learning occur in the form of inner products in $\mathcal{H}$, which allows us to define a kernel function $K(\mathbf{x}_i, \mathbf{x}_j) = \langle \boldsymbol{\phi}(\mathbf{x}_i), \boldsymbol{\phi}(\mathbf{x}_j)\rangle$, and then a non-linear SVM can be constructed using only the kernel function, without having to consider the mapping $\boldsymbol{\phi}$ explicitly. Finally, the decision function implemented by the classifier for any test vector $\mathbf{x}_*$ is given by $f(\mathbf{x}_*) = sgn(\sum_{i=1}^{n} y_i \alpha_i K(\mathbf{x}_i, \mathbf{x}_*) + b)$, where b can be easily computed from the α_i that are neither 0 nor C [6].

In the literature, the RBF kernel is commonly used to define the mapping $K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{1}{2\sigma^2}(\|\mathbf{x}_i - \mathbf{x}_j\|^2\right)$. Despite the good characteristics of this kernel, one can note that no explicit weight is defined for the (in principle) different relevance of each spectral band (feature). A possible solution to alleviate this shortcoming is to tune a different Gaussian width *per* feature, but this results in a too heuristic method, also prohibitive for the hyperspectral scenario. In this paper, we introduce the Mahalanobis kernel (MK) in the formulation of the SVM, which is defined as:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{1}{2\sigma^2}(\mathbf{x}_i - \mathbf{x}_j)^\top \mathbf{Q}^{-1}(\mathbf{x}_i - \mathbf{x}_j)\right), \tag{4}$$

where $\mathbf{Q}$ is the estimated covariance matrix computed using the available training data. Note that this constitutes a non-linear generalisation of the classical Mahalanobis distance metric through the use of the kernel methods framework.

3 Acquisition methodology

Experiments were conducted on 20 mandarins Cv. clemenules and 20 mandarins Cv. clemenvilla. Thirty-two of them were inoculated with spores of Penicillium digitatum sp at a concentration of spores of 10^6 spores/ml and the rest (8), only with water. Later, the fruit was stored at 18ºC and 90% RH. Hyperspectral images were acquired using a monochromatic high-resolution camera on which two liquid crystal tuneable filters (LCTF Varispec Vis-07 and NIR-07) were placed having a spectral resolution of 7 nm and covering the range between 400 to 1100 nm (400 to 720 nm and 650 to 1100 nm, respectively). In order to know the transmittance characteristics of the LCTF in the spectral region of interest, the equipment was calibrated before the experiments using a precision spectrometer and a calibrated light source. A standard white spectralon, and a black sorbothane sheet that absorbs up to 95.5% of light, were also used for reference purposes. The scene was lighted using halogen lamps to obtain good radiance in the visible and NIR spectra.

The inoculated area of every fruit was labelled and imaged at 12-hour intervals until the damage was observed visually. For each fruit, monochromatic images in the 460 to 1020 nm range were acquired at 10 nm intervals, producing $N = 57$ features (spectral channels) per fruit (bands from 400 to 460 and 1020 to 1100 nm were discarded owing to the low efficiency of the filters in these ranges). In order to obtain the actual reflectance of the fruits, corrections were applied to avoid the effect of the spatial inhomogeneities of the lighting system and to correct the spherical shape of the fruits by producing a digital elevation model of the fruits [7].

4 Experimental Results

We built a training and a test set for validating the classification results. The training set contains 4320 pixels; 1920 were from the Cv. clemenules and 2400 from the Cv. clemenvilla, acquired at different stages of the development of the damage. In each window, pixels were labelled as sound/rotten/stem.

We compare performance of linear discriminant analysis (LDA) classifier, a classification tree C4.5 (Tree), and the SVM using both an RBF kernel (RBF-SVM) and a Mahalanobis kernel (MK-SVM). In all cases, the kernel width was tuned in the range $\sigma = \{10^{-3}, \ldots, 10^3\}$, and the regularisation parameter was varied in $C = \{10^{-1}, \ldots, 10^3\}$. A one-vs-one multiclass strategy was followed for training the models. In order to analyse model robustness, we conducted experiments in ill-posed situations, i.e. low number of high-dimensional labelled training samples. We randomly selected different rates of labelled samples (0.1%, 1%, 2%, 5%, 10%, 25%) from the training set and used 8-fold cross-validation for free parameter tuning. Then, we tested the built classifier on the whole images.

Figure 1 shows the obtained results (averaged over 100 realisations). It is worth noting that the proposed kernel method outperforms the rest for both fruit varieties. This improvement is specially significant for the (more complex) clemenules variety where an average gain of 5% in the overall accuracy is obtained, thus suggesting that a proper band selection could improve the results. However, the design and application of a feature selection stage is time-consuming, scenario-dependent, and sometimes needs *a priori* knowledge. The related problem of overfitting in high dimensional input spaces is alleviated with the use of the MK-SVM. The better performance of the method is also observed in the clemenvilla variety, specially in ill-posed situations (0.1% training samples).

The good numerical results obtained with the presented method are confirmed observing the classification maps in Figure 2. Here, the MK-SVM produces spatially more uniform and accurate solutions compared to the rest of classifiers. In general, the rest of the models in homogeneous areas produce many false positives, which is intolerable for operational environments. These problems are more evident in the tree and linear discriminant classifiers, suggesting the problems of overfitting and its Hughes attendant. In conclusion, the robustness to the input data dimensionality observed for the MK-SVM method suggests its potential usefulness for on-line fruit classification and sorting.

5 Conclusions

This work demonstrated the feasibility of a hyperspectral computer vision technique for the detection of infections caused by Penicillium digitatum in citrus fruits before they become apparent. We introduced the use of the Mahalanobis kernel in the SVM classifier to improve results, leading to a more versatile feature-adapted kernel classification scheme. Our future work is tied to introducing the contextual and textural information in the classifier.

Acknowledgments

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References

[1] N. Kondo, U. Ahmad, M. Monta, and H. Murase, "Machine vision based quality evaluation of Iyokan orange fruit using neural networks," *Computers and Electronics in Agriculture*, vol. 29, no. 1-2, pp. 135–147, 2000.

[2] W.M. Miller and G.P. Drouillard, "Multiple feature analysis for machine vision grading of Florida citrus," *Applied Engineering in agriculture*, vol. 17, no. 5, pp. 627–633, 2001.

[3] N. Aleixos, J. Blasco, F. Navarrón, and E. Moltó, "Multispectral inspection of citrus in real time using machine vision and digital signal processors," *Computers and Electronics in Agriculture*, vol. 33, no. 2, pp. 121–137, 2002.

[4] G. Camps-Valls, J. L. Rojo-Álvarez, and M. Martínez-Ramón, Eds., *Kernel Methods in Bioengineering, Signal and Image Processing*, Idea Group Publishing, Hershey, PA (USA), Nov 2006.

[5] T. M. Cover, "Geometrical and statistical properties of systems of linear inequalities with application in pattern recognition," *IEEE Transactions*

on Electronic Computers, vol. 14, pp. 326–334, June 1965, Reprinted in Artificial Neural Networks: Concepts and Theory, IEEE Computer Society Press, Los Alamitos, California, 1992, Eds. P. Mehra and B. Wah.

[6] B. Schölkopf and A. Smola, *Learning with Kernels – Support Vector Machines, Regularization, Optimization and Beyond*, MIT Press Series, 2002.

[7] J. Gómez-Sanchis, E. Moltó, L. Gómez-Chova, N. Aleixos, G. Camps-Valls, F. Juste, and J. Blasco, "Hyperspectral computer vision system for early detection of penicillium digitatum in citrus fruits," in *Proceedings of the XVI CIGR/EurAgEng/VDI-MEG/FAO World Congress 2006 - Agricultural Engineering for a better World*, Bonn, Germany, Sep 2006, pp. ISBN: 3–18–091958–2.

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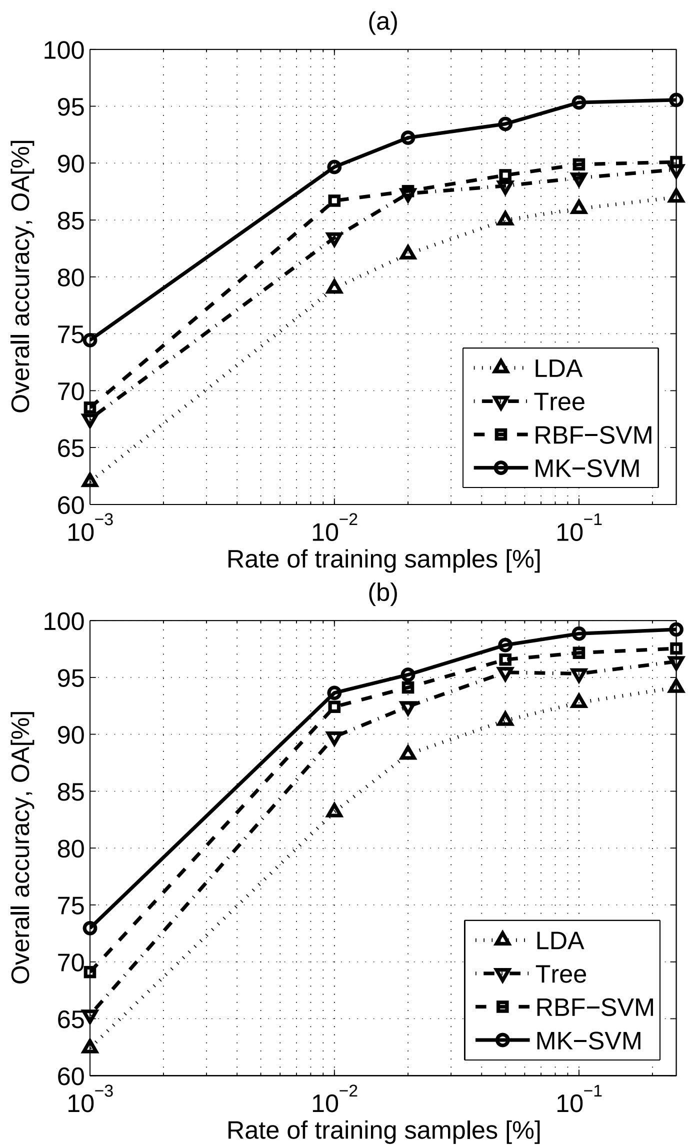

Figure 1: Overall accuracy in the test set for all classifiers using different rates of training samples for (a) clemenules and (b) clemenvilla mandarin varieties.

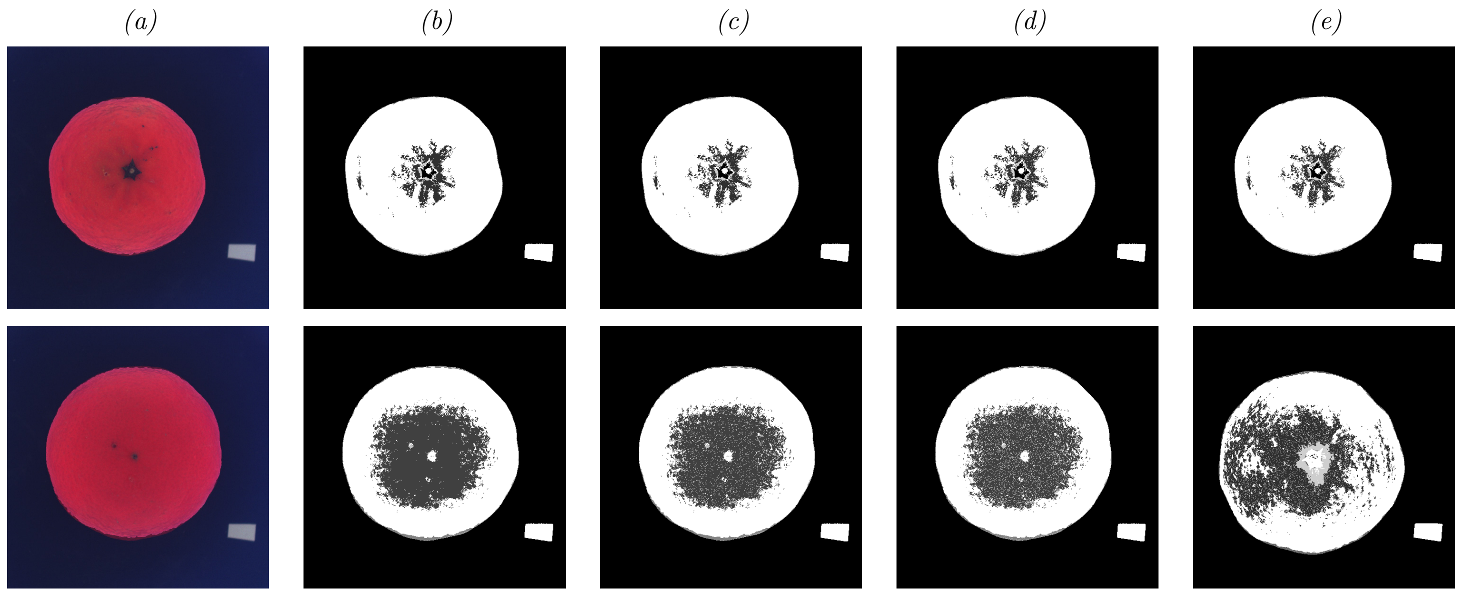

Figure 2: Classification examples for (top) clemenules and (bottom) clemevilla varieties. (a) Pseudocolor image, (b) MK-SVM, (c) RBF-SVM, (d) Tree and (e) LDA classification results. Legend: Black (background), white (sound), dark gray (rotten), light gray (stem).