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WND-CHARM: Multi-purpose image classification using compound image transforms

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ABSTRACT

We describe a multi-purpose image classifier that can be applied to a wide variety of image classification tasks without modifications or fine-tuning, and yet provide classification accuracy comparable to state-of-the-art task-specific image classifiers. The proposed image classifier first extracts a large set of 1025 image features including polynomial decompositions, high contrast features, pixel statistics, and textures. These features are computed on the raw image, transforms of the image, and transforms of transforms of the image. The feature values are then used to classify test images into a set of pre-defined image classes. This classifier was tested on several different problems including biological image classification and face recognition. Although we cannot make a claim of universality, our experimental results show that this classifier performs as well or better than classifiers developed specifically for these image classification tasks. Our classifier's high performance on a variety of classification problems is attributed to (i) a large set of features extracted from images; and (ii) an effective feature selection and weighting algorithm sensitive to specific image classification problems. The algorithms are available for free download from http://www.openmicroscopy.org.

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1. Introduction

The increasing use of digital imagery in many fields of science and engineering introduces a demand for accurate image analysis and classification. Applications include remote sensing (Smith and Li, 1999), face recognition (Shen and Bai, 2006; Jing and Zhang, 2004; Jing et al., 2006; Pentland and Choudhury, 2000), and biological and medical image classification (Boland and Murphy, 2001; Awate et al., 2006; Cocosco et al., 2004; Ranzato et al., 2007). Although attracting considerable attention in the past few years, image classification is still considered a challenging problem in machine learning due to the very complex nature of the subjects in real-life images, making quantitative similarity measures difficult.

A common approach to quantitatively measure similarity between images is to extract and analyze a set of low-level image features (Heidmann, 2005; Gurevich and Koryabkina, 2006). These can include color (Stricker and Orengo, 1995,, 2004, texture (Smith and Chang, 1994, 1996; Livens et al., 1996; Ferro and Warner, 2002), shape (Mohanty et al., 2005), histograms (Flickner et al., 1995; Chapelle et al., 1999; Qiu et al., 2004), and more. However, image features perform differently depending on the image classification problem (Gurevich and Koryabkina, 2006) making the accuracy of a task-specific image classifier limited when applied to a different imaging task.

The performance of task-specific classifiers in problems they were not originally designed for can often be inadequate, introducing a significant barrier to using automated image classification in science and engineering. New image classification problems are continually emerging in these fields, requiring the continual development and optimization of new image classifiers to specifically address these problems. The knowledge and experience needed to successfully implement such vision systems are not typically available to an experimentalist or application developer who does not specialize in image analysis or pattern recognition.

The proliferation of imaging problems and classifiers to address them is acute in the field of cell biology. The range of instrumentation and imaging modes available for capturing images of cells multiplexed with the variety of morphologies exhibited by cells and tissues preclude a standard protocol for constructing problem-specific classifiers. There are very few "standard problems" in cell biology: Identification of specific sub-cellular organelles is an important exception, but the vast majority of experiments where image classification would be an invaluable tool do not fall into standard problem types. The advent of high content screening (HCS) where the goal is to search through tens of thousands of images for a specific target morphology requires a flexible classification tool that allows any morphology to be used as a target. Since

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the variety of target morphologies is vast, a general image classification tool is required to fully exploit the potential offered by HCS.

Here, we describe a multi-purpose image classifier and its application to a wide variety of image classification problems without the sacrifice of classification accuracy. Although the classifier was initially developed to address high content screening, it was found surprisingly effective in image classification tasks outside the scope of cell biology. In Section 2 we describe the features extracted from training and test images, in Section 3 we discuss the high dimensionality classifier that computes similarities between the test and training images, and in Section 4 we present experimental results demonstrating the efficacy of the proposed algorithm in several test cases along with comparisons to previously proposed task-specific classifiers.

2. Image feature extraction

The first step in generalized image classification is to represent the image content as a set of numeric values (features). Due to the wide range of possible tasks performed by generalized image classifiers, the number of features computed during training is far greater than in task-specific classifiers. The types of features used by the image classifier described in this paper fall into four categories: polynomial decompositions, high contrast features, pixel statistics, and textures. In polynomial decomposition, a polynomial is generated that approximates the image to some fidelity, and the coefficients of this polynomial are used as descriptors of the image content. Texture features report on the inter-pixel variation in intensity for several directions and resolutions. High contrast features, such as edges and objects, comprise statistics about object number, spatial distribution, size, shape, etc. Pixel statistics are based on the distribution of pixel intensities within the image, and includes histograms and moments. In addition to calculating these features for the raw image, we subject the image pixels to several standard transforms (Fourier, wavelet, Chebyshev), and calculate features on these transforms, as well as some transform combinations. As will be discussed in Section 4, the discriminating power of these features in many of the tested image sets is greater than features computed from raw pixels.

Together, the feature vector comprises 1025 variables, each of which reports on a different aspect of image content. All features are based on grayscale images, so color information is not currently used. Since we have made no attempt to normalize this variable space, many of these features may be inter-dependent and cannot be considered orthogonal. Furthermore, we make no claim that this feature set is complete in any way. In fact, it is expected that new types of features will be added, which will make this classification approach more accurate, more general or both.

Fig. 1 illustrates the construction of the feature vector by computing different groups of image features on the raw image and on the image transforms (Fourier, wavelet, Chebyshev) and transform combinations. As can be seen in the figure, not all features are computed for each image transform. For instance, object statistics are computed only on the original image, while Zernike polynomials are computed on the original image and its FFT transform, but not on the other transforms. Multiscale histograms, on the other hand, are computed for the raw image and all of its transforms. The permutations of feature algorithms and image transforms was selected intuitively to be a useful subset of the full set of permutations. Evaluation of this subset has established that this combinatorial approach yields additional valuable signals (see Fig. 6). It is quite likely that further valuable signals could be obtained by calculating a more complete set of permutations.

2.1. Basic image transforms

Image features can be extracted not only from the raw image, but also from its transforms (Rodenacker and Bengtsson,

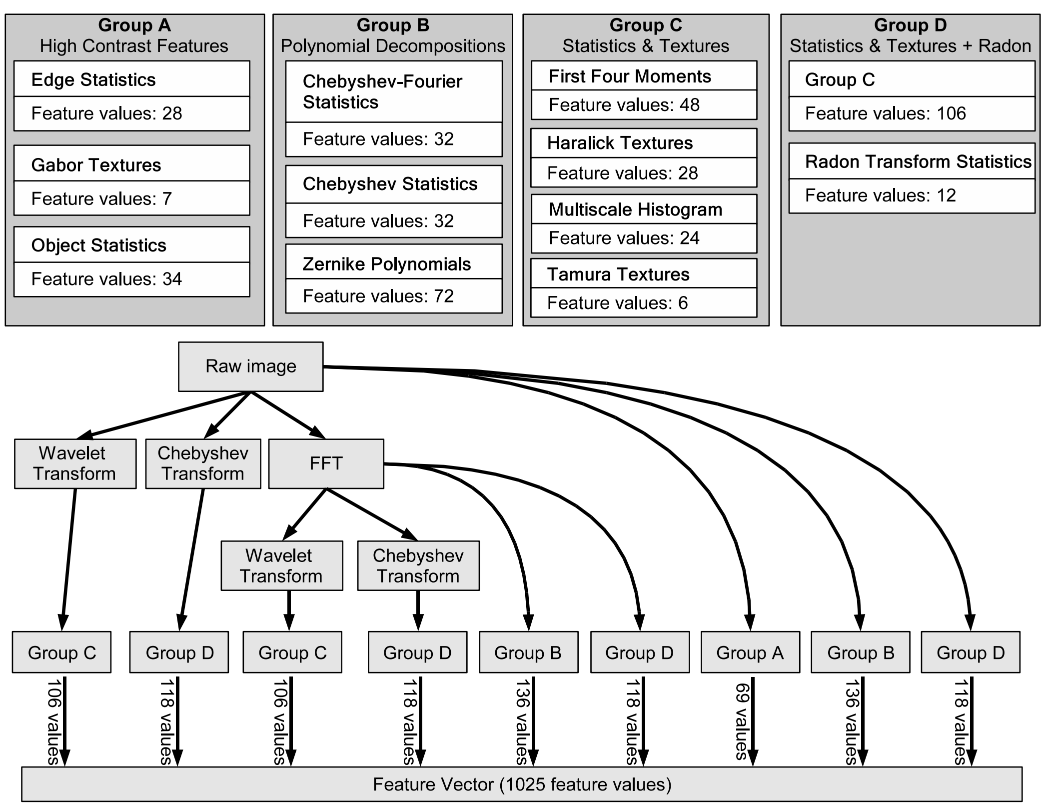

Fig. 1. The construction of the feature vector.