On Contrast-Preserving Visualisation of Multispectral Datasets

Valeriy Sokolov\textsuperscript{1}, Dmitry Nikolaev\textsuperscript{1}, Simon Karpenko\textsuperscript{1}, and Gerald Schaefer\textsuperscript{2}

\textsuperscript{1} Institute for Information Transmission Problems (Kharkevich Institute), Russian Academy of Sciences, Moscow, Russia
\textsuperscript{2} Department of Computer Science, Loughborough University, Loughborough, U.K.

Abstract. Multispectral datasets are becoming increasingly common. Consequently, effective techniques to deal with this kind of data are highly sought after. In this paper, we consider the problem of joint visualisation of multispectral datasets. Several improvements to existing methods are suggested leading to a new visualisation algorithm. The proposed algorithm also produces colour images, compared to grayscale images obtained through previous methods.

1 Introduction

Following the increased need of applications such as remote sensing, multispectral datasets are becoming increasingly common. Consequently, effective techniques to deal with this kind of data are highly sought after, and the development of segmentation and classification techniques based on specific properties of reflection spectra of different objects has been a very active research area in recent years. There is a natural necessity for manual verification of correctness of the results obtained by such algorithms, as well as a necessity for manual choice of areas to be processed.

For example, in the context of remote sensing, a multispectral dataset can be seen as a set of grayscale images representing the same area. Each image of this set corresponds to a small band of the registering spectra. The number of bands varies but may be greater than 200. However, the dimensionality of our human visual system is only 3, and we are therefore not well equipped to perceive such datasets directly. This problem also arises for joint visualisation of images of different origins or modalities, for example visualising physical sensing of micro-samples obtained using fluorescence microscopy.

In this paper, we address the fundamental problem of compound representation of multispectral datasets, i.e. sets of $N$ grayscale images $I(x, y) = (I_n(x, y))$, $n = 1, \ldots, N$ in a form suitable for human perception. That is, we present an effective method for multispectral visualisation. Importantly, such a visualisation is required to preserve local contrast. Moreover, our proposed algorithm produces colour images, compared to grayscale images obtained through previous methods.
2 Related Work

The simplest method for visualising multispectral data is to let the user choose three images from the dataset and unite them into one falsecolour image. However, it is clear that this approach is far from optimal, and that especially when the number of images in the set is large, the number of channels the user is unable to visualise simultaneously is still large.

Another popular method uses averaging to obtain resulting grayscale images. For this, the user specifies a vector of averaging weights $\lambda = (\lambda_1, \ldots, \lambda_N)$. The resulting grayscale image $G(x, y)$ is then obtained by $G(x, y) = I(x, y) \cdot \lambda$. This procedure corresponds to projecting an image vector onto the vector $\lambda$. The disadvantage of this method however is the possibility of losing contrast. If the vectors $I(x_1, y_1)$ and $I(x_2, y_2)$ for neighbour points satisfy the condition $I(x_1, y_1) - I(x_2, y_2) \perp \lambda$ then after averaging we have $G(x_1, y_1) = G(x_2, y_2)$ even if the norm of the difference $\|I(x_1, y_1) - I(x_2, y_2)\|$ is large. Of course, one can choose some other weight vector, but it seems impossible to effectively choose such a vector for all points in a general case.

One can attempt to reduce that disadvantage by choosing the weight vector depending on statistical analysis of the source dataset. One way to achieve this is using principal component analysis (PCA). Considering the source dataset as the set of vectors in some $N$-dimensional vector space, the weight vector is then chosen as an eigenvector corresponding to the largest eigenvalue of the covariance matrix of that set of vectors \[3\].

PCA-based techniques are among the most popular method for processing multispectral datasets. However, in PCA-based visualisations, there is also the possibility of losing local contrast. Let us consider an example with a model dataset of 9 images as input. In every image the intensity of pixels equals 0 for the whole image, except for a small square where the intensity equals 1. The areas of squares are completely disjoint. Hence, one should expect to see 9 squares in the visualisation. However, applying PCA-based visualisation results in an image, shown in Fig. 1, where one of the square is “eliminated” (the bottom right square in Fig. 1).

![Fig. 1. PCA-based visualisation of a dataset of 9 images each containing a square](image)