## Selective Visualization of Anomalies in Fundus Images via Sparse and Low Rank Decomposition

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Figure 1: Representative result of our technique. At left is a monochrome input image of the optic disc, which shows slight cupping. We decompose this input image into a sum of low rank and sparse matrices. The sparse matrix allows us to enhance contrast of the cup and other significant structures.

## 1 Introduction

Anomaly visualization is a well tackled problem in data visualization, especially in the context of image data. Techniques such as local contrast enhancement and histogram equalization have already been extensively explored. These techniques provide a simplistic approach to the problem, and are not geared towards selective enhancement of the anomalies. Recently, advanced segmentation algorithms have been applied, which have been shown to selectively enhance the anomalies. In spite of this, segmentation algorithms tend to be complex and ad-hoc. We provide a new approach to the problem which selectively enhances the anomalies without segmenting the regions.

In our approach, we exploit multiple images (k=10 at minimum), which combine the advantage of machine learning (where data is used constructively) with algebraic operations (rank). As such, we are able to leverage results from unsupervised data which makes the algorithm much more scalable and easier to reproduce. The dataset of healthy images need to be built only once. In contrast to standard supervised learning methods, where a dataset must be curated and the learning algorithm usually involves several tuning parameters.

In this paper, we provide following key insights:

- We relate anomalies in data, specifically in medical images, to breaks in the algebraic matrix structure.
- We show that the algorithm is easily scalable given the unlabeled nature of the data and simple rank constraint.

## 2 Our Approach

Exploiting sparse constraints in real world signals has shaped signal processing research for the last decade. The robust principal component analysis technique as shown in [Candès et al. 2011], combines both sparsity and rank constraints to decompose a matrix into the sum of two matrices, one which is sparse and the other low

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rank. In [Peng et al. 2011], this technique is presented in the context of an important computer vision application which forms the basis for our approach.

We start with a matrix of vectorized grayscale fundus images which define a state of 'normalcy'. Our goal is to enhance the pathological differences between a query image and the database of normal images. Our technique is similar to the atlas based approach, though the difference lies in the fact that our approach is not sensitive to non-pathological changes such as illumination gradients.

The similarity between the images can be expressed in the context of whether one image can be formed by linear combination of other images from the matrix. Assuming similarity across the normal images, the generated matrix is rank deficient. If we include the query image to the generated matrix, we get a new matrix whose rank is the sum of rank of the previous matrix and unity. Therefore, we decompose this new matrix into its corresponding sparse and low rank components. The intuition for decomposing the matrix relies on the fact that abnormalities are sparse in image space. For example, microaneurysms<sup>1</sup> are different from the background, which get translated to the sparse component upon decomposition. Thus, we are able to isolate the abnormalities through low-rank and sparse decomposition.

## References

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