Macular region enhancement of Fundus Fluorescein Angiogram images using super resolution via sparse representation and quality analysis

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Abstract

This paper presents a novel methodology for enhancement of macular region using sparse representation of segmented macular region and super resolution of Fundus Fluorescein Angiogram (FFA) images affected by diabetic maculopathy. The proposed methodology enhances the quality of images which is a necessary step for further analysis of images. The segmented region of the macular region is used to construct a dictionary of patches. These patches can be expressed as a sparse linear combination of an over complete dictionary. The patches of the low-resolution input are taken and the coefficients of the corresponding sparse representations are used to generate the high-resolution output. It has been observed that the proposed image enhancement algorithm achieves better quality of images. The results were evaluated using statistical quality metrics and compared with various interpolation techniques like bilinear and bicubic.

Keywords: Fundus Fluorescein Angiogram, diabetic maculopathy, Macula, Super resolution, sparse representation.
1. Introduction

Diabetic macular edema (DME) is another major reason for low vision and blindness mainly in diabetic population. Visual loss from DME is five times more than that from proliferative diabetic retinopathy (PDR). Identification of macular area of human beings plays an important role in the detection and diagnosis of many eye diseases for opthalmologists. Macular changes can happen during the progress of diabetes mainly associated with non-proliferative diabetic retinopathy (NPDR) or proliferative diabetic retinopathy (PDR). Ophthalmic features of the NPDR include micro aneurysms in the macular area, retinal haemorrhages, hard exudates, retinal edema, cotton-wool spots, venous abnormalities, intra-retinal micro vascular abnormalities and dark-blot haemorrhages. PDR is characterized by proliferation of new vessels from the capillaries which results in the formation of neovascularisation in the optic disc and in the fundus. DME occurs due to increased permeability of the retinal capillaries. Fig.1 shows FFA images for normal and diabetic maculopathy retina. We were successful in segmenting the macular region using a combination of sparse methods and active contour model [1]. We were also successful in applying super resolution to FFA images earlier [2]. The motivation for the proposed approach is as per the requirement of the clinician who wanted to magnify the patterns associated with DME which has not been addressed by the existing technique available in the literature [3].

![Fig. 1: (a) Normal FFA image (b) FFA of a diabetic maculopathy](image)

1. Materials and methods

The data set consisting of FFA images of multiple subjects affected with CSME in the age-group of 20-85 years collected from Amrita Institute of Medical Sciences (Kochi). A set of clinical parameters like age, sex, HBA1C, hemoglobin levels, fasting and postprandial blood sugars have been considered here while collecting the images. The parameters that are crucial for the evaluation of CSME like pattern of macular leakage, presence of PDR and presence of pattern traction with respect to FFA images of both eyes were collected. The clinical impression on the posterior segment was also noted.

2. Methodology

The proposed approach consists of generating a high-resolution image from a low resolution input. The major steps involved in the proposed approach are explained in 3.1

3.1. Algorithm

**Input:** Trained dictionaries of $D_h$ and $D_l$ of segmented macular region of FFA image.

**Output:** The reconstructed high resolution macular region of the input.

Step 1: Patches are generated from this input image.
Step 2: Dictionary learning is applied on the patches as in [4].
Step 3: The higher resolution of the segmented region is generated using the equation given in [5] briefly explained in section 3.2
3.2. Working

The segmented macular region is used to create a dictionary of high-resolution and low-resolution patches denoted by $D_h$ and $D_l$ respectively. For each patch $y$ taken from the upper left-hand corner, the mean pixel value $m$ is computed. The optimization problem with $D$ and $y$ is defined as given in Eq. (1).

$$\min_x \|D - y\|_2^2 + \lambda \|x\|_1$$ (1)

The corresponding high resolution patch is generated using the following Eq. (2).

$$x = D_h \alpha^*$$ (2)

Each high-resolution patch is gathered to generate a high-resolution image $X_0$ using the process of gradient descent. The closest patch to $X_0$ is selected based on the reconstruction constraint given below in the Eq. (3).

$$x^* = \arg \min_x \|SHX - Y\|_2^2 + c\|X - X_0\|_2^2$$ (3)

Where $H$ is the Gaussian filter used and $S$ represents the magnification factor which is being set to two.

4. Results and discussion

The experimental results of super resolution based on the sparse representation of the segmented macular region are as shown in Fig. 2. The results of super resolution were compared with other popular contrast enhancement techniques like CLAHE [6], bilinear and bicubic interpolations [7]. It has been observed that there is a small difference between these three methods and the proposed method worked better than others. The experimental setup consisted of a total of 25 images of size 255 x 255 and the output was reconstructed from the patches and interpolated to 510 x 510. We have done a quality analysis of the reconstructed images using statistical quality matrices like entropy, standard deviation and variance as there were no reference images. The results indicate that the proposed method gives better results than others. Please see Fig. 3, 4 and 5 where the proposed approach has been visualised for a sample subset of five images from the dataset affected with DME.

5. Quality analysis

For measuring the quality of the images, we have taken statistical measures as there were no reference images. The reconstructed images were compared with results of CLAHE, bicubic and bilinear interpolation methods. The different metrics are explained briefly below.

5.1 Entropy

Shannon’s entropy method [8] is a popular statistical measure for evaluating the information content present in the image. The entropy formula is given by Eq. (4)

$$\text{Entropy}(E) = -\sum_{k=2}^{p} p_k \log_2 p_k$$ (4)

Where $p_k$ represents the normalized pixel intensity histogram of selected image and $k$ represents the number of pixels used for histogram equalization.

$$R_E = \text{Entropy of output image} - \text{Entropy of input image}$$ (5)

$R_E$ measures the similarity of the compared images as given in Eq. (5). It is zero when two images are exactly similar. For our images we got a positive result indicating that the resultant reconstructed images are enhanced as
can be seen from Fig. 3 results.

Fig. 2. (a-d) **Input FFA images** with 4 different stages, (e-h) Corresponding **CLAHE** results, (i-l) **Sparse super resolution** method (m-p) **bicubic** interpolation, (q-t) **bilinear** interpolation

5.2 **Standard deviation**

Standard deviation measures the contrast of an image. So it can be used for calculating the quality of an image. This metric would be more efficient in the absence of noise. An image with high contrast would have a high standard deviation [9]. Fig. 4 gives a graphical representation of the results which proves that super resolution method works far better than others.

5.3 **Difference in variance**

The final measure we have computed is called difference in variance (DIV) [10] given by Eq. (6)

\[
\text{DIV} = \frac{\left(\sigma_{\text{input}}^2 - \sigma_{\text{output}}^2\right)}{\sigma_{\text{input}}^2}
\]  

(6)
Where, $\sigma$ represents the variance of the image. As given in Fig. 5, it has been observed that the results are better for reconstructed images using super resolution technique.

![Fig 3. Entropy of sample images](image)

![Fig. 4 Variance of sample images](image)
6. Conclusion
From our experimental results it has been observed that super resolution via sparse representation is applicable to medical images especially macular fundus images which has poor visibility of lesions affected with diabetic maculopathy. Our work has established that enhancement using super-resolution is better when compared to earlier approaches. We have considered a standard dictionary size of 1024. A regularisation parameter of 0.2, up sampling factor of 2. This up sampling factor can be changed to higher values so that the clinician can get better visualisation of the lesions. Our future work is to change these parameters and analyse the results and also to implement this in a GPU based machine to reduce the computation time.

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