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Consensus image method for unknown noise removal

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ABSTRACT

Noise removal has been, and it is nowadays, an important task in computer vision. Usually, it is a previous task preceding other tasks, as segmentation or reconstruction. However, for most existing denoising algorithms the noise model has to be known in advance. In this paper, we introduce a new approach based on consensus to deal with unknown noise models. To do this, different filtered images are obtained, then combined using multifuzzy sets and averaging aggregation functions. The final decision is made by using a penalty function to deliver the compromised image. Results show that this approach is consistent and provides a good compromise between filters.

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1. Introduction

The degradation of an image is unavoidable during acquisition. The restoration of degraded images is an important task widely studied in computer vision [24,33,20,8,18,26,1,15,6,25,13]. It always received a lot of attention from many researchers of different fields. Denoising is one of the most fundamental image restoration techniques [20,8,26,1,15,25,13], due to random distortions which make difficult to perform any required image processing. The desired goals of a denoising algorithm are to completely remove noise, while effective information (edge, corner, texture and contrast, etc.) is preserved, at the same time that artifacts do not appear.

In order to find an ideal image denoising algorithm, researchers have proposed hundreds of algorithms. The most popular noise assumption is the additive Gaussian noise [24,33,8]. However a Gaussian noise assumption is too simplistic for most applications, specifically for medical and astronomical images [20]. In the particular case of medical images, in computer tomography (CT), the decay of the signal is better modeled with a Poisson distribution [27,16,18]. Other medical images, as single-photon emission computed tomography (SPECT) or positron emission tomography (PET), can also be well modeled with a Poisson distribution [23,25]. In the case of magnetic resonance images (MRI), a Rice distribution better models the abnormalities in the image for a single-coil [5,1].

Despite different approaches that exist in order to reduce noise, all of them fail in their performance with images owning a noise distribution for which these algorithms are not optimal. It would be desirable to have a denoising algorithm being able to deal with any noise distribution. However this is a complex issue due to the different nature of the images (e.g. CT capturing process is different from the digital camera). Therefore, this work is focused on the fusion of a set of filtered images, through a multifuzzy set, previously filtered from a noisy image with unknown noise distribution. We select filters existing in the literature that are optimal for a concrete noise. In particular, filters for impulse, Poisson, Gaussian and Rician noise are applied. Then, the fusion is carried out using consensus via penalty functions on a cartesian product of lattices, where the penalty function chooses the value that minimizes the error for each pixel in accordance to the different options.

Fig. 1 shows graphically the proposed schema. Starting from the noisy image I_N, the first step is to build a multifuzzy set from the filtered images, in our case (FI_1, FI_2, FI_3, FI_4), so each pixel (i, j) is represented by several values (each value corresponds to pixel (i, j) of each filtered image). But, we need to obtain a fused image, I_{result}, with only one value for each pixel. For this reason we continue by using averaging aggregation functions. However, we do not know which is the best function to use. To solve this problem, we select a set of functions. In this paper we decide to use OWA operators. In particular, OWA operators constructed from fuzzy quantifiers, since they provide a more flexible knowledge representation than classical logic, that it is restricted to the use of only two quantifiers, *there exists* and *for all* [12]. We select three different OWA operators, namely 'at least half', 'most of them' and 'as many as possible' because of their good performance. We apply these operators to each pixel, so we obtain three new possible

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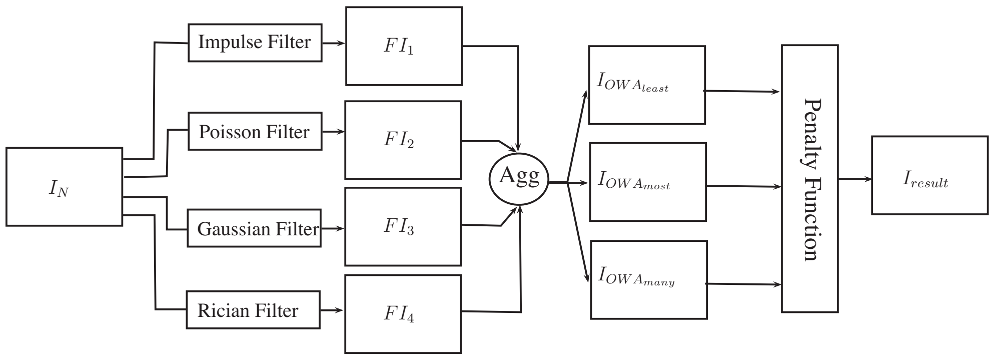

Fig. 1. Schema consensus algorithm.

values for each pixel ($I_{OWA_{least}}, I_{OWA_{most}}, I_{OWA_{many}}$). In order to decide the best aggregated value among them, we use penalty functions that take the value that minimizes the error with respect to the filtered images, and thus, the best fused image is obtained, I_{result}. Our aim is to obtain consistent and stable results, regardless of the image nature (e.g. CT, MRI, digital image). One of the applications of this work is with MRI, because they present a more sophisticated noise model than a simple Gaussian noise, it however can be applied to other images with different nature as it is also shown.

The paper is composed as follows: Section 2.1 introduces the different noise models and filters. In Section 2.2, multifuzzy sets are explained. Then, Section 3 presents the idempotent functions, their properties and a specific case: the OWAs operators, a family of idempotent averaging functions. Penalty functions and the consensus algorithm are explained in Section 4. Finally, in Sections 5 and 6 specific results and a final conclusion are exposed.

2. Construction of multifuzzy sets from a set of filtered images

Given an unknown noisy image, our first step consists in associating a multifuzzy set composed by several images. Each one of these images will be obtained by applying some filter optimized for a certain type of noise.

2.1. Noise models and filters

Many digital image devices often produce a degradation in the image quality. This noise is mainly introduced during the image capturing (sensors, amplifiers), the transmission or the recording [21], although in some modalities, as CT or MRI, it can also be introduced in the reconstruction algorithm [3]. This can e.g. be caused by dust sitting on the lens, by a dissipation in the electronic components or by electromagnetic distortions during transmission. Digital imaging techniques must deal with the degradations present in the images.

Each element involved in the pipeline used to obtain the final (reconstructed) image (sensors, lens, A/D converter, enhancement algorithm, reconstruction algorithm, etc.), influences the noise characteristics. Several approaches exist that deal with Gaussian or impulse noise [24,33,8,26], although in some cases these are simple approximations compared to the real noise that is presented. For instance, MRI, specifically MR magnitude image, are mainly characterized by Rician noise, although this noise is dependent on the number of coils or the reconstruction method [3]. Furthermore CT, PET, SPECT or astronomical images are identified by Poisson noise [27,23,16,20,18,25].

Different filters are applied in this work with the aim to prove the effectiveness of consensus, and how it can help to obtain a good performance. The selected filters cover different approaches to the image denoising problem, as well as they perform better for a specific noise distribution. We give an overview of the characteristics of these filters.

The first approach tackles the problem of impulse noise, and uses the DBAIN filter proposed by [26]. The algorithm, in a first step detects if a processed pixel is noisy or noise-free depending on its occurrence in a corresponding window. If the pixel is determinated as corrupted, then the pixel is replaced by the median value of the window. Although, in case the median is considered corrupted, instead of the median, it is replaced by the value of neighborhood pixels. This method does not require any parameter for its performance.

Additive white Gaussian noise (AWGN) has generally been found to be a reasonable model for noise originating from electronic amplifiers. The considered filter to deal with white Gaussian noise has been the approach proposed by Goossens et al. [15]. This filter is based on the non-local means (NLmeans) filter proposed by Buades et al. [8]. This version of NLmeans improves the original version, dealing with noise in non-repetitive areas with a post-processing step and presenting a new acceleration technique that computes the Euclidean distance by a recursive moving average filter. Moreover, they introduce an extension that can deal with correlated noise. However, its performance depends on a previous configuration. The standard deviation estimation, the searching window or the block size needs to be defined previously. We use the configuration from the original paper for our experiments.

The approach used to estimate Rician noise, the probability density function that mainly characterizes MRI in single-coil systems [5,3], is proposed by Aja-Fernandez et al. [1]. This filter adapts the linear minimum mean square error (LMMSE) to Rician distributed images. Moreover, noise estimation can be automatically calculated based on local statistics. Although the version used in our experiments is the approach in which the standard deviation is given as an input.

Finally, for Poisson noise, an extension of the NLmeans is proposed for images damaged by Poisson noise. Deledalle et al. [13] propose to adapt the similarity criteria of NLmeans algorithm to Poisson distribution data. For this filter, a previous configuration is required. For our experiments, the used parameters are those suggested in the original article, as the algorithm is tuned to obtain good results.

2.2. Multifuzzy sets

Once the set of filtered images is obtained, we represent them by means of multifuzzy sets, in which each element is given by a set of n memberships, taking n as the number of filters. A unique multifuzzy set is built with all the elements of the images.

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