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● *Original Contribution*

ULTRASOUND IMAGE DESPECKLING BASED ON STATISTICAL SIMILARITY

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Abstract—Ultrasound images are affected by the speckle phenomenon, a multiplicative noise that degrades image quality. Several methods for denoising have been proposed in recent years, based on different approaches. The so-called non-local mean is considered the state-of-the-art method; the idea is to find similar patches across the image and exploit them to regularize the image. The method proposed here is in the non-local family, although instead of partitioning the target image in patches, it works pixelwise. The similarity between pixels is evaluated by analyzing their statistical behavior, in particular, by measuring the Kolmogorov–Smirnov distance between their distributions. To make this possible, a stack of acquired images is required. The proposed method has been tested on both simulated and real data sets and compared with other widely adopted techniques. Performance is interesting, with quality parameters and visual inspection confirming such findings. (E-mail: fabio.baselice@uniparthenope.it or fabase@gmail.com)

Key Words: **Speckle, Noise reduction, Non-local mean, Spatial filter, Ultrasound images, Image processing.**

INTRODUCTION

Because of the nature of the acquisition system, ultrasound (US) images are affected by the speckle phenomenon. The random scattering variability makes the received echoes characterized by non-constant intensity, producing low-contrast and degraded images, typically with a granular appearance. This is commonly considered a noise source, and much effort has been expended to reduce speckle intensity Burckhart (1983).

In recent years, several methods have been proposed for removing speckle, belonging to different filtering families (Baselice et al. 2018; Joel and Sivakumar [2013]). An overview of the more interesting methods can be found in Yahya et al. (2014). A very effective approach is the so-called non-local mean (NLM) (Buades et al. 2010). In brief, this method assumes that images contain a large number of similar regions, commonly referred to as similar patches, positioned at different locations across the image. Once identified, such patches are jointly exploited to obtain a regularized version of the image (Katkovnik et al. 2009). Of course, a similarity criterion must be chosen to identify such patches. The effectiveness of the filter is related mainly to the validity of the adopted similarity metric (Foi and Boracchi 2016). Several metrics have been proposed, spanning from the weighted Euclidean distance (Buades et al. 2005) to the foveated distance (Foi and Boracchi 2016). The general idea consists of selecting two patches, overlapping them and computing the mean of the difference after the application of a weighting kernel or other operator types.

In this article, a new similarity metric is introduced, based on evaluation of the statistical distance instead of the Euclidean distance. In greater detail, the metric is based on evaluation of the cumulative distribution functions (CDFs) of the data and on computation of the Kolmogorov–Smirnov distance (Massey 1951). Of course, the CDFs are not *a priori* known and must be estimated from the acquired data. In the following, the proposed approach is referred to as the Kolmogorov–Smirnov non-local mean (KS-NLM).

The main advantage of this method is the ability of working pixelwise instead of dividing the image in patches, removing the ghost effect that often affects images filtered with NLM algorithms (Martino et al. 2014;

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Pierazzo et al. 2014). On the other hand, the principal drawback is the requirement for a stack of data to provide an effective CDF estimation, as required by the KS test. In the case of US data, this requirement can easily be achieved by acquiring several frames of a video within a limited time. In the following, we illustrate that frames acquired in less than 2 s are enough for the methodology to work effectively.

The KS-NLM method has been compared with other widely adopted denoising filters, belonging to the NLM as well as other families, producing effective regularization in both simulated and real data sets. Compared with Euclidean distance-based metrics, the proposed metric has been found to be more robust with respect to the noise and the differences among the textures of the acquired image.

The article is organized as follows. In the next section, the KS-NLM method is described. The simulated and real frameworks for performance evaluation, together with comparisons with other widely adopted filters, are presented under Results. Results achieved and conclusions drawn are covered in the last two sections.

METHODS

Acquisition model

Let us consider a video composed of several frames acquired by an ultrasound (US) scanner. The following multiplicative noise model for the amplitude signal $z(x, r, t)$ can be assumed as

$$z(x,r,t)=y(x,r,t)n(x,r,t),\ x\in X,\ r\in R,\ t\in T,\ \{X,R,T\}\subset\mathbb{R} \tag{1}$$

where $y(\cdot)$ is the noise-free signal, $n(\cdot)$ is the speckle noise, (x, r) are the space indexes related to the acquisition geometry defined in domains X and R, respectively, and t is the acquisition time, which assumes values in domain T. The noise $n(\cdot)$ can be considered Rayleigh distributed. Although this assumption is valid only in tissues with several similar small scatterers within the resolution cell, it is commonly adopted Yahya et al. (2014).

Non-local approach

Approaches belonging to the non-local mean family divide the noisy image $z(\cdot)$ in patches and evaluate the similarities among them (Buades et al. 2010). Given a pixel $z(x, r, t)$ and a neighboring system $\Delta=\{\Delta_x,\Delta_r,\Delta_t\}\subset\mathbb{R}^3$, its surrounding patch is defined as

$$\mathbf{z}_{x,r,t}(\Delta)=z(x+\delta_x,r+\delta_r,t+\delta_t),\ \delta_x\in\Delta_x,\ \delta_r\in\Delta_r,\ \delta_t\in\Delta_t \tag{2}$$

The defined patch is compared with the other patches within a searching window (which could also be the whole image). A metric is defined for measuring the mutual distance d between the textures of two different patches. Generally, a Euclidean distance is adopted, with a windowing kernel for introducing different weights into the patch pixels Buades et al. (2005):

$$d(\mathbf{n_1},\mathbf{n_2})=\left\|(\mathbf{z}_{\mathbf{n}_1}(\Delta)-\mathbf{z}_{\mathbf{n}_2}(\Delta))^2\mathbf{k}\right\|_1 \tag{3}$$

Here, $\mathbf{n_1}$ and $\mathbf{n_2}$ are the two patch center locations (x_1, r_1, t_1) and (x_2, r_2, t_2), and $\mathbf{k}$ is the windowing kernel.

Different operators for measuring patches similarity have been proposed, with the intent of improving the accuracy of lowering the computational burden (Foi and Boracchi 2016; Froment 2014; Tasdizen 2009; Torre et al. 2009).

Once similar patches have been found across the searching window, each with a similarity index, they all are properly merged to produce the regularized image $\hat{y}(\mathbf{n}_1)$, as illustrated in Figure 1.

The fusion step takes into account the distance found for each similar patch

$$\widehat{y}(\mathbf{n_1})=\sum_{\mathbf{n}_2\in\{X,R,T\}}z(\mathbf{n_2})qe^{-d(\mathbf{n_1},\mathbf{n_2})} \tag{4}$$

where q is a normalization term. From eqn (4), it is clear that the larger the number of similar patches found, the stronger is the filtering efficacy.

Although NLM approaches are capable of strong and effective regularization performance, they are also characterized by some drawbacks. In particular, the typical artifacts that affect NLM filtered images are commonly referred to as ghosts, structured signal-like patches that appear mainly in flat areas, originating from random noise and reinforced through the patch selection process (Dabov et al. 2007; Dai et al. 2013; Martino et al. 2014; Pierazzo et al. 2014).

Proposed approach

On the basis of NLM theory, a novel approach to speckle filtering is proposed. Specifically, a different similarity measurement is proposed based on the statistical distributions of pixels. The underlying assumption is the availability of a stack of images of the same scene with different noise realizations. Within the US framework, this stack could be available in the hypothesis that several video frames are acquired. Of course, minimal movement of the probe and the body is mandatory, but this requirement can easily be achieved considering that US systems acquire tens of frames within a second. Under this assumption, the noise-free signal $y(\cdot)$ can be considered time independent, modifying eqn (1) into

$$z(x,r,t)=y(x,r)n(x,r,t) \tag{5}$$