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Sparse Representation in 2-D Ultrasound Image of Heart

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Abstract: To reduce energy minimization in 2D ultrasound images of cardiac motion, the input images are loaded with multiplicative Rayleigh noise .Spatial smoothness is done by sparse representation after the images are segmented into a number of pixel elements via patch. Dictionary learning is the next step to regularize the obtained solution. This proposed work provides accuracy and strain errors, then compare with state of the art algorithm. Furthermore, it is denoised by K-SVD to get an accurate clear image.
Keywords: Dictionary Learning , Images , Pixel ,Ultrasound

I. INTRODUCTION

It is therefore of critical importance to improve techniques of cardiac function assessment, thus facilitating diagnosis and treatment of these diseases. There are a variety of methods used to evaluate the health of the heart. Among the non-invasive techniques, medical imaging is used to assess its mechanical action by means of various modalities such as magnetic resonance imaging (MRI) and ultrasound imaging (UI). However, because of its relatively high temporal resolution, UI is more adapted to the rapid motion of the heart. In addition, it presents advantages such as low budget requirements and reduced discomfort for the patient. This makes UI, particularly echocardiography, the most widely used modality in cardiology. Furthermore, the acquired ultrasound (US) images provide information that is essential for cardiac function evaluation. US images can be exploited either through direct visualization or using post processing methods that extract valuable qualitative and measurable features. In this context, 2D automatic cardiac motion estimation as well as the associated strain measurements have been proved to be efficient tools for the diagnosis of cardiovascular diseases [2]–[6]. Cardiovascular diseases have become a major healthcare issue. Improving the diagnosis and analysis of these diseases have thus become a primary concern in cardiology. The heart is a moving organ that undergoes complex deformations. Therefore, the quantification of cardiac motion from medical images, particularly ultrasound, is a key part of the techniques used for diagnosis in clinical practice. Thus, significant research efforts have been directed toward developing new cardiac motion estimation methods. These methods aim at improving the quality and accuracy of the estimated motions. However, they are still facing many challenges due to the complexity of cardiac motion and the quality of ultrasound images. Recently, learning-based techniques have received a growing interest in the field of image processing. More specifically, sparse representations and dictionary learning strategies have shown their efficiency in regularizing different ill-posed inverse problem

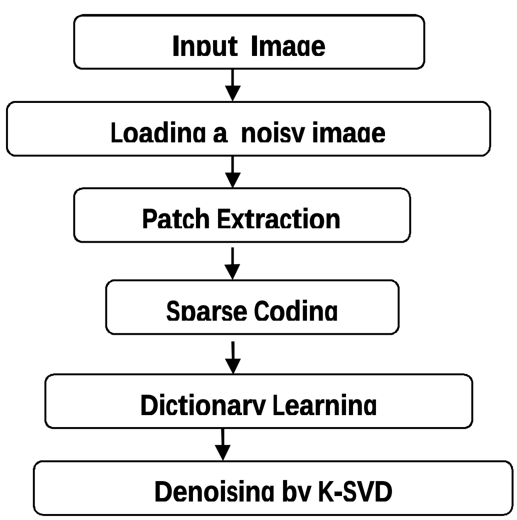

Fig 1 Sparse Representation In 2-D Ultrasound Image Of Heart

II. LITERATURE SURVEY

A. Sparse Representation

In narrow sense, a sparse representation of data is a representation in which few parameters or coefficients are not zero, and many are (strictly) zero.The dictionary is computed by a random selection of patches.Fourier is a sparse representation for sines or close-to-sine signals. Conversely, a zero signal, except for a few values, is sparse in its original domain.

B. Dictionary Learning

Adjusts the image by manipulating the rarity of dictionary atoms. Firstly, learn the dictionary through sparse coding algorithms on divided sub-image blocks. Secondly, compute the rarity of dictionary atoms on statistics of the corresponding sparse coefficients. Thirdly, adjust the rarity according to specific application and form a new dictionary. Finally, reconstruct the image using the updated dictionary and sparse coefficients.

C. State-of-the –art Algorithm

It is used to compare the performance evaluation or it is used to compare the classifier technique.We compare the proposed approach with three state-of-the art motion estimation methods.

1) *Block-Matching:* we consider the block-matching algorithm using the NCC similarity measure .For each patch, a full-grid search is conducted in a defined searching window.Moreover,spatial regularization is induced in post processing By the cubic interpolation used to derive sub-pixel valued displacements and dense motion fields. Note that block-matching algorithms are also referred to as speckle tracking methods in the US literature.
2) *B-spline:* in order to evaluate the performance of the sparsity-based regularization term, we consider the method studied in the algorithm of uses the same similarity measure (CD2) and spatial regularization as the proposed method.
3) *Monogenic Signal:* this method uses the monogenic phase in order to construct the similarity measure and considers a local offline motion model,without any additional spatial regularization. It corresponds to the method of for which the intensity-based similarity measure has been replaced by a spatial phase-based metric.

III. PROPOSED METHODOLOGY

In this work, we present a new method for cardiac motion estimation in 2D ultrasound images. The proposed method combines a specific similarity measure with spatial smoothness and sparse regularizations, exploiting jointly the statistical nature of B-mode images, the smoothness and the sparse properties of cardiac motion. The data fidelity term considered in this work is based on a multiplicative Rayleigh noise model [2] The spatial smoothness is ensured by a regularization based on the gradient of the motion vector. Moreover, we promote the use of a regularization exploiting a sparse representation of motion based on DL using patterns of cardiac motion. In the sparse coding step associated with motion estimation, the dictionaries are learned using the ground-truth displacements of realistic simulations.

IV. RESULTS AND DISCUSSION

Medical devices have been developed which can detect these minor fluctuations in the patient and communicate this information directly to healthcare providers who can take appropriate action. Creating this seamless link between patients,their implants,and devices which relay patient data and physicians is essential. Evolving technology in the telemetry space is making it possible to make smart, timely healthcare decisions. For future work, it would be necessary to investigate possible extensions of the algorithm to 3D UI. In this work, we have addressed the problem of 2D motion estimation, which can present some shortcomings, such as out-of-plane motion and limited geometrical information, that could be overcome in 3D. Nevertheless, it should be pointed out that in contrast with 2D imagery, 3D UI is affected by the problems of frame rate and image spatial resolution in the azimuthal direction and thus, does not necessarily provide better motion estimation results.

V. CONCLUSIONS

The proposed method also regularized the motion by using a regularization smoothing term based on the gradient of the motion field and by exploiting a sparse motion prior based on DL. Our results showed the effectiveness of these regularizations for cardiac motion estimation. In terms of motion and strain accuracy, the results obtained with highly realistic simulations demonstrated the competitiveness of this approach with respect to state-of-the-art methods. The results obtained on real data suggested that the method is consistent with a clinical interpretation related to images of healthy and pathological subjects.

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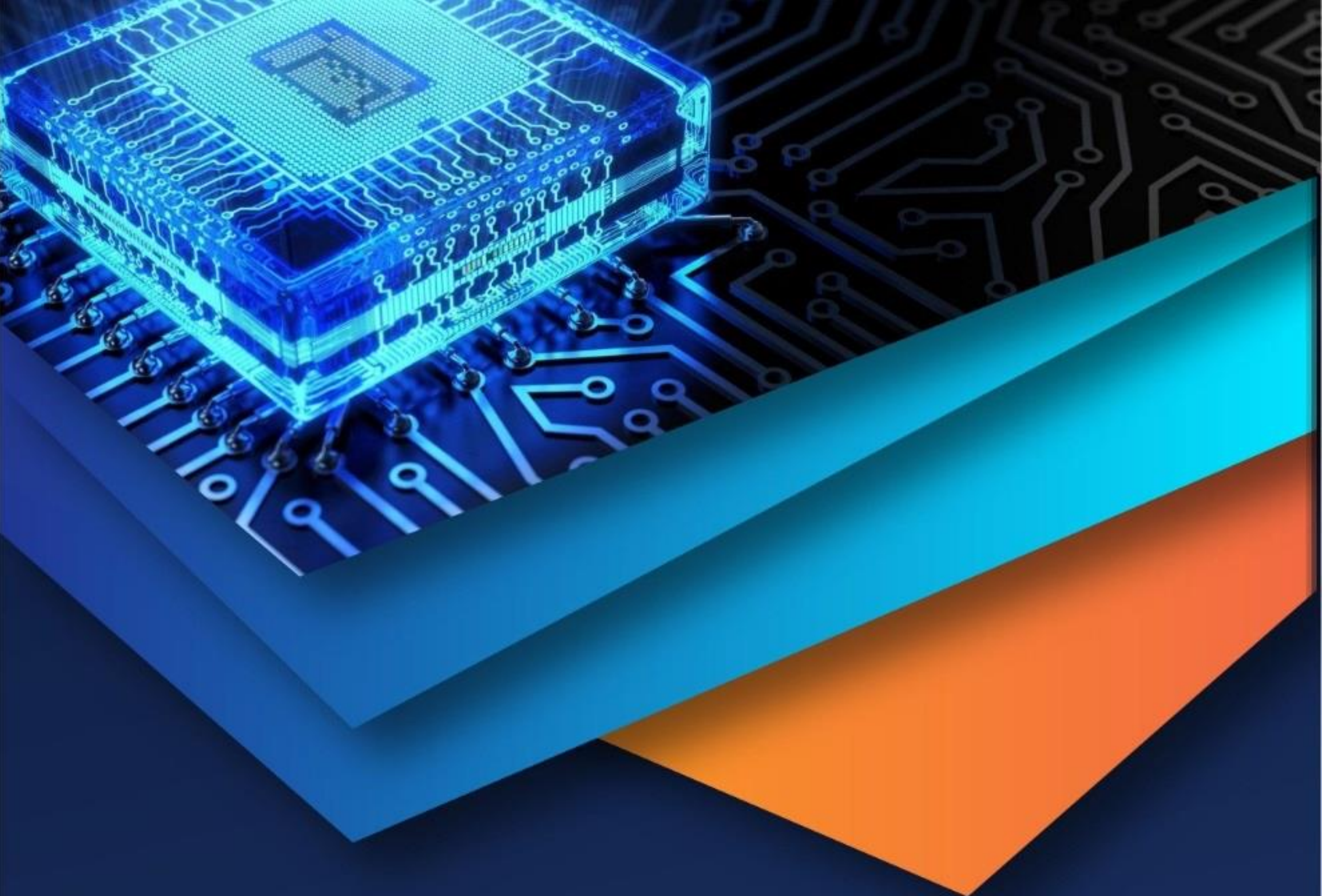

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