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CARDIAC MOTION ESTIMATION WITH DICTIONARY LEARNING AND ROBUST SPARSE CODING IN ULTRASOUND IMAGING

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ABSTRACT

Cardiac motion estimation from ultrasound images is an ill-posed problem that needs regularization to stabilize the solution. In this work, regularization is achieved by exploiting the sparseness of cardiac motion fields when decomposed in an appropriate dictionary, as well as their smoothness through a classical total variation term. The main contribution of this work is to robustify the sparse coding step in order to handle anomalies, i.e., motion patterns that significantly deviate from the expected model. The proposed approach uses an ADMM-based optimization algorithm in order to simultaneously recover the sparse representations and the outlier components. It is evaluated using two realistic simulated datasets with available ground-truth, containing native outliers and corrupted by synthetic attenuation and clutter artefacts.

***Index Terms*—Cardiac motion estimation, dictionary learning, robust sparse coding, anomaly detection.**

I. INTRODUCTION

According to the World Health Organization, cardiovascular diseases are the leading cause of death in the world. Analyzing the cardiac motion is of key importance for the early detection and prevention of these diseases. In particular, useful information about abnormal motion patterns can be extracted by analyzing the deformation of the heart throughout the cardiac cycle.

There are a variety of medical imaging modalities used for motion analysis such as magnetic resonance imaging (MRI), computed tomography (CT), single-photon emission CT (SPECT), positron emission tomography (PET) or ultrasound imaging (UI). Even though conventional UI presents challenges, such as a high noise level, it is still the most commonly used modality in cardiology. The wide use of ultrasound is due to its low budget requirements, high accessibility, real-time acquisition, portability, non-ionization and the reduced discomfort for the patient. In the context of cardiology, ultrasound not only allows us to capture the shape and size of the heart, but also its typical or abnormal ventricular deformations and strain rates [1], [2].

Because of the major impact of the local analysis of the cardiac deformation on the diagnosis and treatment choice, there is a growing need for developing new motion estimation techniques that limit the loss of structural and local information. Most of the methods used for cardiac motion estimation belong to one of the following three categories: optical flow, speckle tracking or elastic image registration. In optical flow algorithms, the motion of the heart is computed using the velocities of the brightness patterns. These methods assume that the illumination is constant between consecutive images [3], [4]. However, this assumption rarely holds for 2D UI, which is highly affected by noise and out-of-plane motions. In elastic registration algorithms, the image characteristics can be exploited to define a specific similarity measure. The mapping between pairs of images is achieved using a non-rigid geometric transformation (*e.g.*, B-splines [5], [6]). Finally, speckle tracking-based techniques aim at matching patches between two images at different time instants [7]. The matching criterion is usually built using the statistical properties of the images [8].

Motion estimation is an ill-posed problem, in the sense that it does not have a unique solution. In order to overcome this issue, additional constraints are used to regularize the solution. Several regularization approaches have been proposed in the literature, for example, based on parametric models (affine, B-splines) or using the interpolation of coarse motion fields to dense grids. Recently, the interest of imposing patch-based sparsity of cardiac motion fields in appropriate overcomplete dictionaries has been shown [9]. This paper improves the method of [9] by robustifying the sparse coding step. More specifically, we assume that the local cardiac motion patterns to be estimated can be expressed as a linear combination of a few atoms in an overcomplete dictionary. We then address the problem of joint sparse coding and detection of anomalies, i.e., motion patterns that significantly deviate from the expected model [10].

The remainder of the paper is structured as follows. Section II presents a brief overview of the dictionary learning-based cardiac motion estimation method of [9]. Section III summarises the theory related to robust sparse coding with anomaly detection proposed in [10]. Section IV provides details about the proposed cardiac motion estimation algorithm. Finally, experimental results and conclusions are reported in Sections IV and V.

II. CARDIAC MOTION ESTIMATION USING SPARSE REPRESENTATION AND DICTIONARY LEARNING

The goal of a sparse representation is to express cardiac motion patches $\boldsymbol{u}_p \in \mathbb{R}^n$, extracted from the dense motion field to be estimated $\boldsymbol{u} \in \mathbb{R}^N$, as a linear combination of a few elements of a dictionary $\boldsymbol{D} \in \mathbb{R}^{n \times q}$, *i.e.*,

$$\boldsymbol{u}_p \approx \boldsymbol{D}\boldsymbol{\alpha}_p \tag{1}$$

where $\boldsymbol{\alpha}_p \in \mathbb{R}^q$ is a sparse vector and $q > n$. The learning of a dedicated overcomplete dictionary can be performed either offline, using a set of ground-truth motions, or online, using the current estimation. In this paper, two dictionaries have been trained offline using highly realistic simulated motion fields [11]. The resulting dictionaries allow us to capture typical patterns of vertical and horizontal cardiac motions. The dictionary learning problem for motion estimation can be formulated as follows

$$\min_{\boldsymbol{D},\boldsymbol{\alpha}_p} \sum_p \|\boldsymbol{P}_p \boldsymbol{u_t} - \boldsymbol{D}\boldsymbol{\alpha}_p\|_2^2 \text{ subject to } \forall p, \|\boldsymbol{\alpha}_p\|_0 \leq K \tag{2}$$

where $\boldsymbol{P}_p \in \mathbb{R}^{n \times N}$is a binary operator that extracts the pth patch from a set of training motion fields $\boldsymbol{u_t}$, $\boldsymbol{\alpha}_p$ is the sparse coefficient vector associated with the pth patch and K is the maximum number of non-zero coefficients. A classical way of solving this problem is by alternating between a sparse coding step (where $\boldsymbol{D}$ is fixed and the vectors $\boldsymbol{\alpha}_p$ are estimated) and a dictionary update step (where $\boldsymbol{\alpha}_p$'s are fixed and the dictionary $\boldsymbol{D}$ is updated).

As explained in Section I, the motion estimation problem is ill-posed. Therefore, additional constraints are required for its regularization such as constraining the estimation to a specific type of displacements. In [9], these constraints were incorporated in a regularization term denoted as E_{reg}. The motion fields are finally obtained through the minimization of an appropriate energy function as follows

$$\min_{\boldsymbol{\alpha}_p,\boldsymbol{u}} [E_{\text{data}}(\boldsymbol{u}) + E_{\text{reg}}(\boldsymbol{u}, \boldsymbol{\alpha}_p)] \tag{3}$$

where E_{data} is the data fidelity term, which is based on the assumption of a Rayleigh distributed speckle noise [12], and E_{reg} combines two types of regularizations, *i.e,*

$$E_{\text{reg}}(\boldsymbol{u}) = \lambda_d \sum_p \|\boldsymbol{P}_p \boldsymbol{u} - \boldsymbol{D}\boldsymbol{\alpha}_p\|_2^2 + \lambda_s \|\nabla \boldsymbol{u}\|_2^2 \tag{4}$$

where ∇ denotes the gradient operator and λ_s, λ_d are positive hyperparameters that balance the influence of the regularization terms. Note that the first term in (4) expresses the patch-wise sparsity of the motion field $\boldsymbol{u}$ in the learned dictionary $\boldsymbol{D}$ and that the second term imposes spatial smoothness using the standard ℓ_2-norm total variation. Since the problem (4) is hard to solve directly, an alternate optimization scheme can be adopted. More specifically, the sparse coding problem is first solved for a fixed $\boldsymbol{u}$. In a second step, the obtained sparse codes $\boldsymbol{\alpha}_p$ are fixed, and the motion field $\boldsymbol{u}$ is updated [9]. Note that after a few iterations, the sparsity of the estimated motion patches is enforced by increasing the value of λ_d [9].

III. ROBUST SPARSE CODING

Anomaly detection refers to the problem of finding abnormal patterns in a dataset. In this work, the anomalies consist of cardiac motion patches that do not have a sparse representation in the dictionary (*i.e.,* (1) is not satisfied). For example, anomalies can occur on anatomical boundaries, which are characterized by a discontinuous motion, or in regions affected by artefacts (*e.g.*, attenuation or clutter). In this work, we propose to detect such anomalies using the robust sparse coding model studied in [10]. More specifically, this robust sparse coding model assumes that anomalies are sparse, and thus, each patch of motion is approximated by the sum of its sparse representation and an anomaly component as follows

$$\boldsymbol{U} = \boldsymbol{D}\boldsymbol{A} + \boldsymbol{E} + \boldsymbol{V} \tag{5}$$

where $\boldsymbol{U} \in \mathbb{R}^{n \times N_p}$ contains N_p patches of motion of size n, $\boldsymbol{A} \in \mathbb{R}^{q \times N_p}$ are the corresponding sparse codes, the matrix $\boldsymbol{E} \in \mathbb{R}^{n \times N_p}$ denotes the anomalies that are possibly affecting the motion patches and $\boldsymbol{V} \in \mathbb{R}^{n \times N_p}$ is the additive Gaussian noise. We assume there are few anomalies in the dataset, i.e., that the matrix $\boldsymbol{E}$ is sparse with only few non-zero columns.

In [10], the sparse codes $\boldsymbol{A}$ and anomalies $\boldsymbol{E}$ were estimated jointly by solving the following optimization problem

$$\begin{aligned} \{\widehat{\boldsymbol{A}}, \widehat{\boldsymbol{E}}\} = \min_{\boldsymbol{A},\boldsymbol{E}} \|\boldsymbol{U} - \boldsymbol{D}\boldsymbol{A} - \boldsymbol{E}\|_F^2 \\ \text{subject to } \|\boldsymbol{A}\|_0 < N_p K \\ \|\boldsymbol{E}\|_{2,0} \leqslant L \end{aligned} \tag{6}$$

where $\|\boldsymbol{E}\|_{2,0}$ counts the number of non-zero columns in $\boldsymbol{E}$ and L is the maximum number of anomalies. The problem (6) promotes a sparse representation for most of the motion patches in $\boldsymbol{U}$ and admits a maximum of L anomalies, i.e., a maximum of L non-zero columns in $\boldsymbol{E}$. This problem can be solved using the alternating direction method of multipliers (ADMM) as explained in [10].

IV. CARDIAC MOTION ESTIMATION WITH ROBUST SPARSE CODING

In this work, we propose to combine the cardiac motion estimation method of [9] with the robust sparse coding algorithm of [10]. In [9], the sparse coding step was solved using the OMP algorithm. In this work, this step is replaced by the robust sparse coding problem (6), which allows us to automatically mitigate the impact of anomalies. As in [10], the robust sparse coding step is solved using ADMM after relaxing the ℓ_0 pseudo-norm to the convex ℓ_1-norm. The problem (6) is thus reformulated as follows

$$\min_{\boldsymbol{A},\boldsymbol{E}} \frac{1}{2} \|\boldsymbol{U} - \boldsymbol{D}\boldsymbol{A} - \boldsymbol{E}\|_F^2 + \beta \|\boldsymbol{A}\|_{1,1} + \gamma \|\boldsymbol{E}\|_{2,1} \tag{7}$$

where $\beta \in \mathbb{R}$ and $\gamma \in \mathbb{R}$ are two scalars controlling the sparsity of $\boldsymbol{A}$ and the column-wise sparsity of $\boldsymbol{E}$. In order to solve (7), an auxiliary variable $\boldsymbol{Z}$ is introduced leading to the equivalent problem

$$\min_{\boldsymbol{A},\boldsymbol{E},\boldsymbol{Z}} \frac{1}{2}\|\boldsymbol{U} - \boldsymbol{D}\boldsymbol{A} - \boldsymbol{E}\|_F^2 + \beta\|\boldsymbol{Z}\|_{1,1} + \gamma\|\boldsymbol{E}\|_{2,1}$$
$$\text{subject to } \boldsymbol{Z} = \boldsymbol{A}. \tag{8}$$

The reader is invited to consult [10] for further details about the way of solving (8). The resulting cardiac motion estimation algorithm using robust sparse coding is detailed in Algorithm 1. Note that this algorithm estimates the motion field using the implicit Euler time marching method as in [13].

Algorithm 1 Motion field estimation using robust sparse coding

Input: $\boldsymbol{D}$, λ_s, λ_d, $OuterSteps$, $InnerSteps$

Initialize: $\boldsymbol{U} = 0$
for $i = 1$ To $OuterSteps$ **do**
  for $j = 1$ To $InnerSteps$ **do**
    % Sparse coding with anomaly detection
    $(\boldsymbol{A}_j, \boldsymbol{E}_j) \leftarrow \min_{\boldsymbol{A},\boldsymbol{E}} \frac{1}{2}\|\boldsymbol{U} - \boldsymbol{D}\boldsymbol{A} - \boldsymbol{E}\|_F^2 + \beta\|\boldsymbol{A}\|_{1,1} + \gamma\|\boldsymbol{E}\|_{2,1}$

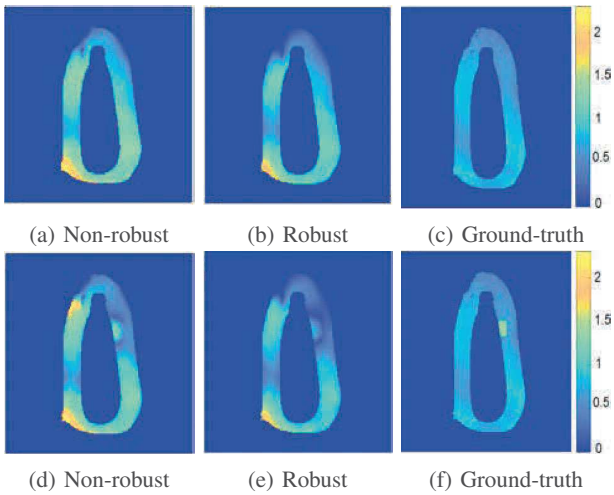
    % Motion estimation
    $\boldsymbol{u_j} \leftarrow \min_{\boldsymbol{u}} E_{data}(\boldsymbol{u}) + \lambda_d \sum_p \|\boldsymbol{P}_p\boldsymbol{u} - \boldsymbol{D}\boldsymbol{A}_{p,j}\|_2^2 + \lambda_s\|\nabla\boldsymbol{u}\|_2^2$
  end for
  % Increase λ_d
end for

Output: estimated motions $\boldsymbol{u}$, sparse codes $\boldsymbol{A}$ and anomalies $\boldsymbol{E}$.

V. EXPERIMENTAL RESULTS

This section evaluates the performance of the proposed motion estimation method based on a robust sparse coding step (referred to as Robust) in comparison to the standard sparse coding approach obtained for $\boldsymbol{E} = \boldsymbol{0}$ (referred to as Non-robust). The experiments were conducted on a dataset of highly realistic simulations with an available ground truth (i.e., with known motion vectors) [14]. The sequences contain 34 images that span a full cardiac cycle. In a first step, the LADdist sequence was used to learn the dictionaries. The considered algorithms were then evaluated both on a native sequence (*i.e.,* LADprox) and on the same sequence corrupted with synthetic attenuation and clutter artefacts. For both methods, all the hyperparameters were tuned to minimize the root mean square error between the estimated and ground-truth motion fields leading to $\lambda_s = 0.1$ for both methods and $\beta = 0.05$, $\gamma = 0.1$ for the robust sparse coding approach. The dictionary learning and sparse regularization parameters were adjusted as in [9].

Fig. 1 shows the ground-truth and estimated motions for the 4th frame of the sequences (corresponding to the maximum average displacements in the systole phase). This figure shows that the obtained motion fields are overall similar for the native sequence, while some differences can be observed for the corrupted one, particularly, around the attenuation artefact.



(a) Non-robust (b) Robust (c) Ground-truth

(d) Non-robust (e) Robust (f) Ground-truth

Fig. 1: Ground-truth and estimated motions (in pixels) for the 4th frame of (a,b,c) the native sequence and (d,e,f) the corrupted sequence.

In order to examine the local behavior of the proposed algorithm, the error maps of the displacement estimates of the 4th frame are shown in Fig. 2. These error maps show that the proposed method results in a global decrease of the errors for both sequences. In particular, the errors are smaller for the corrupted sequence around the synthetic attenuation and clutter artefacts. Fig. 2 (c,f) also show that these synthetic artefacts, as well as some motion discontinuities in the myocardial boundaries (near the valves), are captured in the anomaly matrix $\boldsymbol{E}$. Note that the vertical and horizontal anomaly matrices $\boldsymbol{E}_x$ and $\boldsymbol{E}_y$ were merged in this figure such that $\boldsymbol{E} = |\boldsymbol{E}_x| + |\boldsymbol{E}_y|$.

Tab. I provides some quantitative results for the robust cardiac motion estimation algorithm in terms of the global means and standard deviations of the errors (in pixels). This table shows that the robust sparse coding step results in a slight gain in performance for the considered sequences when compared to the non-robust method, with the advantage of detecting and localizing the anomalies.

VI. CONCLUSIONS

This paper introduced a robust cardiac motion estimation method for ultrasound images using a regularization based on a sparse representation and dictionary learning. A robust sparse coding step allowed us to detect and discard abnormal

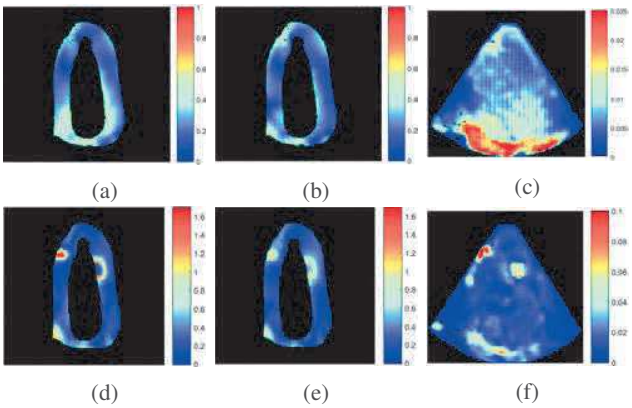


Fig. 2: Motion error maps for (a,d) the native sequence and (b,e) the corrupted sequence with the corresponding anomaly matrices $\boldsymbol{E}$ (for (c) the native and (f) the corrupted sequences).

	Non-robust	Robust
LADprox	0.16 +/- 0.09	0.15 +/- 0.08
Corrupted	0.19 +/- 0.16	0.18 +/- 0.14

Table I: Average means and standard deviations of the errors for the native and corrupted sequences.

motion patches. Our experimental results showed that the proposed approach results in a slight gain in performance when compared to the non-robust method. It also has the advantage of automatically detecting anomalies such as clutter, attenuation or motion boundaries that usually affected cardiac motion estimation algorithms. An interesting perspective would be to robustify the other terms of the cost function, *i.e.*, the data fidelity and the spatial regularization terms as in [15].

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