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Monitoring temperature in additive manufacturing with physics-based compressive sensing

Yanglong Lu, Yan Wang*

Woodruff School of Mechanical Engineering, Georgia Institute of Technology, United States

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ABSTRACT

Sensing is one of the most important components in manufacturing systems to ensure the high quality of products. However, the deployment of a large number of sensors increases the costs of manufacturing systems for both operation and maintenance. Processing the large amount of sensor data for real-time process monitoring is also challenging. Recently compressive sampling or compressed sensing (CS) approaches have been developed to reduce the amount of data collection. However, the reduction is limited to individual sensor types and compression ratio is not high. In this paper, a physics-based compressive sensing (PBCS) approach is proposed to improve the traditional CS approach based on the physical knowledge of phenomenon in applications. The volume of data and the number of sensors needed for process monitoring are significantly reduced. This approach is applied to monitor the temperature field of additive manufacturing processes. In the experimental study, only a few number of thermal readings are needed to reconstruct the complete three-dimensional temperature field using the PBCS approach.

1. Introduction

Sensors have become indispensable for increasingly complex manufacturing processes to ensure high quality of products. In many cases, the process becomes so complex that it completely relies on in-situ sensors to provide online monitoring. There are two major challenges for the “sensor dependency”. The first one is the life-cycle cost of sensors. The cost portion of sensing system installation, operation, and maintenance in the overall cost of manufacturing is rising. More importantly, the reliability of sensors will easily become the weakest link of the reliability of complex systems with a large number of sensors onboard. As a result, the maintenance cost of sensing subsystems is likely to be a major portion of system life-cycle costs. Furthermore, undetected faulty sensors provide inaccurate information and can lead to costly wrong decisions. The second challenge is the bandwidth limitation of communication for the volume of data to be transmitted to enable remote monitoring, diagnostics, and control. Although sensor technologies will gradually become more affordable, communication channels will always be the bottleneck to realize industrial scale Internet of Things or Industry 4.0, where the large volume of data being constantly generated can be easily wasted without being shared in time and used for their original purposes of control and decision making. The scalability of sensor networks as the number of sensors rapidly grows is a major issue of the emerging intelligent and advanced manufacturing systems.

Given the above challenges of applying large-scale and ubiquitous sensing systems in manufacturing, can we develop new protocols to collect and share information more efficiently without relying on current practice of “what you see is what you collected”? More specifically, can we obtain high-fidelity information from the data collected with low-fidelity low-cost sensing systems without deploying a large number of high-resolution high-end sensors? There is a practical need of deploying the minimum number of sensors to effectively monitor system performance. Reducing the number of sensors can improve the cost-effectiveness for system monitoring and control. Reducing the amount of data in communication without sacrificing the amount of information exchanged will also enable us to build scalable sensing and communication networks.

In the most recent decade, a new sampling and data collection approach, compressive sampling or compressed sensing (CS), was developed. CS is a new approach to generate a signal by taking advantage of sparsity so that the amount of collected data can be largely reduced. The main idea is to collect a small set of samples and recover the original signal computationally from these samples. More specifically, if the signal can be represented in the reciprocal space with only a small number of coefficients through transformation, e.g. Fourier and wavelet transforms, then when the signal is projected linearly into a different space with a much lower dimension, the original signal can be

* Corresponding author at: 801 Ferst Drive NW, Atlanta, GA 30332-0405, United States.
E-mail address: yan.wang@me.gatech.edu (Y. Wang).

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recovered, even without much knowledge of projection. The recovery can be fairly precise when the number of non-zero coefficients in the reciprocal space is small (i.e. *sparse*) and the transformation and projection operations are not correlated (i.e. *incoherent*).

Different from traditional CS techniques developed for generic one- or two-dimensional (2D) signals without the consideration of application domains, which are pure data-driven approaches, here a physics-based compressive sensing (PBCS) approach is proposed, which relies on the domain knowledge of specific applications. It is believed that the physical knowledge of the phenomenon that we would like to observe can potentially help us to design more efficient and accurate compressive sensing protocols.

If the original signal has a size of N and its representation in the reciprocal space is sparse with only K non-zero coefficients ($K < N$), standard CS for generic signals allows for robust recovery from $M = O(K\log(N/K))$ measurements. That is, with M measured data points in the order of $K\log(N/K)$, the original data with size N can be recovered. The compression ratio is N/M. The latest development for images (i.e. 2D signals) has reduced M further to $M = O(K)$.

In this paper, we will demonstrate that the proposed PBCS can significantly further improve the compression ratio based on the physical knowledge of the system. Here, the generic PBCS formalism is proposed and applied to monitor the temperature distribution in additive manufacturing (AM) process. In AM processes such as powder bed fusion and material extrusion, materials are locally heated, melt, and solidified to build free-form geometries layer-by-layer. Material phase transition processes (sintering, melting, crystallization, solidification, etc.) are critically dependent on the spatial temperature distribution and its temporal evolution. Therefore, controlling the temperature distribution in the materials is one of the most important factors to ensure the build quality in AM.

The novelty of the proposed PBCS is that it significantly improves compression ratio from traditional CS by incorporating the prior knowledge of physical quantities to be monitored. It is shown that a 3D temperature field can be monitored by the reconstruction from only a few number of single-probe thermal readings. The compression ratio can be improved by two orders of magnitude from the traditional CS with the similar accuracy.

In the remainder of the paper, the background of CS, its application in machine condition monitoring, and inverse heat transfer problem is given in Section 2. The generic framework of PBCS is proposed in Section 3. The setup of experiments for demonstration is described in Section 4. The applications of PBCS in 2D and 3D temperature field reconstructions are demonstrated in Section 5.

2. Background

2.1. Compressed sensing or compressive sampling (CS)

Compressed sensing or compressive sampling [1,2] was initially developed to solve the inverse problem of information recovery purely based on statistical characteristics of signals. Suppose that the original signal is represented in a discrete format as vector. It can be represented in the reciprocal space via transformation as $\boldsymbol{s} = \boldsymbol{\Psi\alpha}$ where $\boldsymbol{\Psi}$ is the matrix representation of transformation (or basis matrix) and $\boldsymbol{\alpha}$ is the vector of coefficients. The size of the original signal vector $\boldsymbol{s}$ is N. The size of the coefficients $\boldsymbol{\alpha}$ could be similar to N, however, only K of them are non-zero ($K < N$). That is, $\boldsymbol{\alpha}$ is K-sparse. When the signal is projected into another space to $\boldsymbol{y} = \boldsymbol{\Phi s}$ with a reduced dimension M ($M < N$) via a projection (or measurement) matrix $\boldsymbol{\Phi}$. The recovery of the original signal from the measured data is to solve the linear equations $\boldsymbol{y} = \boldsymbol{\Phi s} = \boldsymbol{\Phi\Psi\alpha} = \boldsymbol{\Theta\alpha}$. Loosely speaking, because of the K-sparsity, solving $\boldsymbol{\Theta\alpha} = \boldsymbol{y}$ first to find $\boldsymbol{\alpha}$ then reconstructing the original signal by $\boldsymbol{s} = \boldsymbol{\Psi\alpha}$ provides more accurate recovery than solving $\boldsymbol{\Phi s} = \boldsymbol{y}$ to find $\boldsymbol{s}$ directly. CS has been extensively applied in signal processing [3,4], image processing [5,6,7], networked sensing [8], and others.

Various solving procedures for CS problems have been developed. These approaches include convex relaxation (e.g. basis pursuit (BP) [9], LASSO [10], LARS [11], nuclear norm minimization [12]), greedy iteration algorithms (e.g. matching pursuit [13], orthogonal matching pursuit (OMP) [14], regularized OMP [15], stagewise OMP [16], CoSaMP [17], subspace pursuit [18], gradient projection [19], orthogonal multiple matching pursuit [20]), iterative thresholding algorithms (e.g. soft thresholding [21], hard thresholding [22], sparse recovery [23], sequential sparse matching pursuit [24]), combinatorial and sublinear algorithms (e.g. Fourier sampling algorithm [25], HHS [26]), non-convex minimization (e.g. [27], FOCUS [28], iterative regularization algorithm [29], and others.

2.2. Application of classical CS in machine condition monitoring

Recently, CS started being used to monitor machine health conditions. Chen et al. [30] used it to extract impulse components of roller bearing vibration signals. Wang et al. [31] applied to time-frequency sparse representation of gear box vibration signals. Wang et al. [32] applied it to down sampling of bearing vibration signals. Tang et al. [33] classified the faults of rotating machinery with compressed measurements. Ding and He [34] applied to noise removal in the time-frequency domain. Yuan and Lu [35] applied CS to identify the health states of rolling bearing based on compressed vibration signals. Liu et al. [36] demonstrated the feasibility of using compressed features to identify rolling bearing states from acoustic emission signals.

To improve the performance, researchers also trained and optimized the basis/transformation matrix so that higher sparsity of the reciprocal coefficients can be achieved. The training process was also called the dictionary learning, which has been based on the maximum likelihood [30], least-square error [37,34], and hidden Markov model [38].

All of the above approaches applied classical data-driven CS to machine condition monitoring. Signals were generally treated in the same way as any other type of data without the consideration of domain specific knowledge.

2.3. Inverse heat transfer problem

Here the proposed PBCS is to reconstruct temperature distributions from limited measurements by solving the inverse problem. Some limited efforts have been given to study the inverse heat transfer problem [39], which is to estimate unknown quantities including boundary conditions of radiation [40] and convection [41,42], thermophysical properties, initial condition, source terms, and geometry [43] of a heated body with transient temperature measurements. Generic optimization techniques such as adjoint local search, conjugate gradient method [44], genetic algorithm [45] have been applied. The performance of these methods is sensitively dependent on the number of unknown parameters to be estimated. Excursion and oscillation of the solution may occur when the number of parameters is large.

In contrast, the proposed PBCS relies on the sparsity of the coefficient vector in the sense of CS to solve the inverse problem. If the vector to be recovered has a high level of sparsity, it is shown that CS can be very efficient and also provide very accurate results. In PBCS formulation, the knowledge of physical models is used to identify the sparsity that is inherent in the models, such as boundary conditions in heat transfer problems so that PBCS can take advantage of sparsity for robust reconstruction.

3. Proposed PBCS mechanism

The proposed PBCS approach is to reduce the operational cost of the sensing system by using low-fidelity measurements to obtain high-fidelity information, for example, using single probe based measurements (e.g. thermocouple, or noncontact pyrometer) to measure the complete temperature distribution, or using the low-resolution thermal