Computers and Electronics in Agriculture 138 (2017) 117–126

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Inline discrete tomography system: Application to agricultural product inspection

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ARTICLE INFO

Article history:
Received 3 May 2016
Received in revised form 18 April 2017
Accepted 20 April 2017

Keywords:
Computed tomography
Discrete tomography
Inline scanning geometry

ABSTRACT

X-ray Computed Tomography (CT) has been applied in agriculture engineering for quality and defect control in food products. However, conventional CT systems are neither cost effective nor flexible, making the deployment of such technology unfeasible for many industrial environments. In this work, we propose a simple and cost effective X-ray imaging setup that comprises a linear translation of the object in a conveyor belt with a fixed X-ray source and detector, with which a small number of X-ray projections can be acquired within a limited angular range. Due to the limitations of such geometry, conventional reconstruction techniques lead to misshapen images. Therefore, we apply a Discrete Tomography reconstruction technique that incorporates prior knowledge of the density of the object's materials. Moreover, we further improve the reconstruction results with the following strategies: (i) an image acquisition involving object rotation during a linear translation in the conveyor-belt; and (ii) an image reconstruction incorporating prior knowledge of the object support (e.g., obtained from optic sensors). Experiments based on simulation as well as real data demonstrate substantial improvement of the reconstruction quality compared to conventional reconstruction methods.

1. Introduction

X-ray images, also referred to as radiographs, allow nondestructive visualization of the objects interior. Conventional X-ray radiography has been extensively used in inspection and quality assurance of agricultural products on a conveyor belt. A typical example is food inspection for detecting defects or foreign objects (*e.g.*, insect pests, stones, glass, metal parts) (Ayalew et al., 2004; Jiang et al., 2008; Chuang et al., 2011; Mery et al., 2011).

While X-ray radiographs provide some information about the internal structure of objects, one of the major disadvantages of traditional radiography is that it cannot provide quantitative 3D information about the object to be scanned. Indeed, by analyzing only a single X-ray radiograph, it is impossible to obtain depth information that allows to quantify, for example, the pore distribution in food materials. Computed Tomography (CT), in which multiple projections are acquired from the target object and then mathematically combined, is more suited for this purpose. X-ray CT is a useful tool in agriculture engineering (Nicolaï et al., 2014; Herremans et al., 2014; Cantre et al., 2014; Barcelon et al., 1999; Lammertyn et al., 2003; Neethirajan et al., 2008; Dhondt et al., 2010; Janssens et al., 2016). Unfortunately, conventional CT systems are very expensive and require long acquisition times. As a result, the deployment of such technology is not feasible for many industrial environments.

Acceleration techniques have been introduced to improve the throughput of conventional CT systems. Some approaches include the reduction of the amount of data to be reconstructed by using adaptive region of interest tomography (Yang et al., 2011), or the usage of Graphical Processing Unit (GPU) to accelerate the algorithm's computation time (Okitsu et al., 2010). Jiang et al. (2012) exploited both approaches to speed up CT reconstruction for wheat tiller inspection. On the other hand, higher throughput may be achieved by using a non-conventional scanning geometry, which includes a circular array of X-ray sources and detectors with no

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http://dx.doi.org/10.1016/j.compag.2017.04.010
0168-1699/

moving parts, referred to as Real Time Tomography (RTT) (Thompson et al., 2015; Morton et al., 2009; Perry and Gamble, 2001). However, such X-ray systems are very expensive because of the multiple X-ray sources.

This work proposes a static setup, illustrated in Fig. 1, which comprises a single wide cone X-ray source and a large detector for imaging objects passing on a conveyor belt. In this scenario, the scanning process is cheaper and faster than in conventional CT systems. However, the constraints associated to the limited angular range and the number of available projections, besides the existence of truncated data, can lead to significant misshapen images if conventional reconstruction techniques are used. Those irregular structures that may arise in the reconstruction images are commonly referred to as artifacts. In fact, the reconstruction of CT images from missing projection data is a hot topic in the field (Singh et al., 2008; Lu et al., 2010; Lu et al., 2011; Xu et al., 2012; Batenburg et al., 2013; Bieberle and Hampel, 2015; Kobayashi and Tanaka, 2015; Chen et al., 2015). Prior knowledge about the scanned object is often incorporated to compensate the limited projection data in CT reconstructions. In this work, the Discrete Algebraic Reconstruction Technique (DART) (Batenburg and Sijbers, 2011) is used. DART has successfully been applied in conventional CT (Dabravolski et al., 2004; Van de Casteele et al., 2017) and in electron and X-ray diffraction tomography (Batenburg et al., 2009; Batenburg et al., 2010; Zhuge et al., 2017). It incorporates specific prior knowledge related to the scanned materials densities. Even from a limited amount of data, DART is able to reduce the occurrence of artifacts.

Moreover, we applied two strategies to improve the quality of CT reconstructions in such inline scanning setup. The first approach rotates the object during a linear translation in the conveyor-belt to allow a full angular view and to avoid non-sampled projection angles, which are also referred to as missing wedges. The proposed design can be adjusted to operate with a number of different food products. The second approach consists of including optical sensors in the proposed setup to detect the outer shape of the objects passing on the conveyor belt. This information can be used as prior knowledge to restrict the reconstruction domain according to an Expected Object Domain (EOD). In this work, we also propose the EOD-DART which is a domain constrained version of DART.

Preliminary work on using Discrete Tomography in an inline scanning system was introduced in Alves Pereira et al. (2014). This paper extends our previous paper (Alves Pereira et al., 2014) in many ways: (i) evaluation of a novel strategy which allows object rotation with linear translation in the conveyor belt; (ii) experiments including real data; (iii) usage of a more restrictive X-ray fanbeam opening angle and number of projections; (iv) comparison with the Filtered Back Projection (FBP) reconstruction technique; (v) study of influence of variation in system's parameters (*e.g.*, angular range and number of iterations) to the final solution.

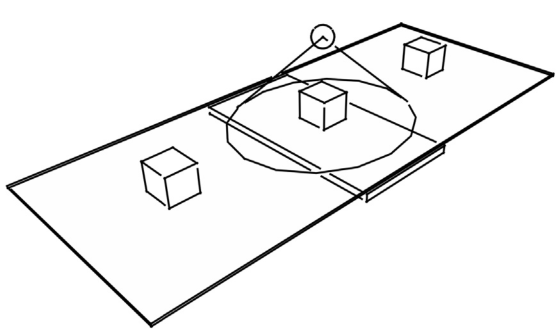

Fig. 1. Overview of the proposed inline scanning geometry: a wide cone X-ray source and a large detector are fixed for imaging objects passing on a conveyor belt.

This paper is organized as follows: Section 2 describes the theory related to the iterative reconstruction techniques, Section 3 presents the simulated scanning geometries and the EOD-DART algorithm, Section 4 shows the results obtained in the experiments and discusses the results, and Section 5 concludes the paper.

2. Algebraic Reconstruction Methods

Presently, Filtered Back Projection (FBP) is the most commonly known reconstruction method because it is simple and fast. However, FBP assumes the availability of a high number of projections, and an equi-angular spacing between them. Since the proposed inline scanning geometry must use a low number of X-ray projections to ensure a fast image process and limited angular view, FBP reconstructions tend to be highly degraded in this inline geometry.

On the other hand, Algebraic Reconstruction Methods (ARM), which cast the reconstruction problem into a system of linear equations, can be applied to different scanning geometries, and they can easily be augmented with object's prior knowledge to compensate a lack of scanned data. If $\mathbf{v} \in \mathbb{R}^N$ is the vector associated with the reconstructed image, and the vector $\mathbf{p} \in \mathbb{R}^M$ denotes the projection data of the scanned object, one can write:

$$\mathbf{p} = \mathbf{W}\mathbf{v} \tag{1}$$

where $\mathbf{W}_{M\times N}$ is the projection matrix, which maps the vector representing the image in the reconstruction domain into the projection domain. Each element $w_{m,n}$ in $\mathbf{W}$ defines the contribution of voxel n in $\mathbf{v}$ to the detector cell m in $\mathbf{p}$. An estimate of $\mathbf{v}$ can then be found by minimizing the following function (Buzug, 2008):

$$\chi^2 = |\mathbf{W}\mathbf{v} - \mathbf{p}|^2 \tag{2}$$

2.1. Simultaneous Iterative Reconstruction Technique (SIRT)

An approximated solution to the least squares problem presented in (2) can be found by applying SIRT. It is a reconstruction technique that iteratively updates partial solutions $\mathbf{v}^{(k)}$ where k denotes the iteration number. Assuming the typical initialization $\mathbf{v}^{(0)} = \mathbf{0}$, each SIRT iteration consists of three steps:

1. Compute the forward projection of the current solution:

$$\mathbf{p}^{(k)} = \mathbf{W}\mathbf{v}^{(k)} \tag{3}$$

2. Compute the *residual sinogram*:

$$\mathbf{r}^{(k)} = \mathbf{p} - \mathbf{p}^{(k)} \tag{4}$$

3. Update the reconstruction image $v^{(k)}$ by adding a weighted backprojection of the *residual sinogram* to the current solution:

$$\mathbf{v}^{(k+1)} = \mathbf{v}^{(k)} + \mathbf{C}\mathbf{W}^T\mathbf{R}\mathbf{r}^{(k)} \tag{5}$$

where $\mathbf{R} \in \mathbb{R}^{m\times m}$ is a diagonal matrix with elements $r_{ii} = 1/\sum_j w_{ij}$. Likewise, $\mathbf{C} \in \mathbb{R}^{n\times n}$ is a diagonal matrix with elements $c_{jj} = 1/\sum_i w_{ij}$. The SIRT reconstruction process ends when a given convergence criterion is met.

2.2. Discrete Algebraic Reconstruction Technique (DART)

If there are only few X-ray projections $\mathbf{p} \in \mathbb{R}^M$ available to reconstruct the image $\mathbf{v} \in \mathbb{R}^N$, *i.e.* $M \ll N$, the solution space of the minimization problem (2) is infinitely large. The idea behind using prior knowledge in the reconstruction process is to reduce the solution space by constraining the set of possible solutions. DART (Batenburg and Sijbers, 2011), for instance, assumes that