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Image and Vision Computing 23 (2005) 441–451

image AND vision COMPUTING

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A wavelet-based multiresolution edge detection and tracking

Ming-Yu Shih, Din-Chang Tseng*

Institute of Computer Science and Information Engineering, National Central University, Chung-li 320, Taiwan, ROC

Received 17 July 2002; received in revised form 6 April 2004; accepted 8 November 2004

Abstract

A gradient image describes the differences of neighboring pixels in the image. Extracting edges only depending on a gradient image will results in noised and broken edges. Here, we propose a two-stage edge extraction approach with contextual-filter edge detector and multiscale edge tracker to solve the problems. The edge detector detects most edges and the tracker refines the results as well as reduces the noised or blurred influence; moreover, the extracted results are nearly thinned edges which are suitable for most applications. Based on six wavelet basis functions, qualitative and quantitative comparisons with other methods show that the proposed approach extracts better edges than the other wavelet-based edge detectors and Canny detector extract.

Keywords: Edge extraction; Edge detection; Edge tracking; Wavelet transform

1. Introduction

Edge detection is a traditional problem with numerous applications in image analysis and computer vision [19]. In the medical applications, many high-level tasks are initialized by the edge information such as, automatic object detection, organ model reconstruction, and isosurface reconstruction from medical images [14,15,18,21]. Before reconstructing 3D human organ models, we must segment each cross-section image, extract the organ contours, and then mesh contour strip between adjacent slice images. Up to the present, we still spend much time in the interactive image post-processing even if many edge detectors have been proposed. The main problems are: (i) the extracted edges are broken, (ii) meaningless thread lines are branched from the actual edges, (iii) different tissues blend each other and then bring blurred edges, and (iv) small blood vessels present isolated sparkles in the slice images. Most edge detectors cannot produce suitable edges for the following processes. Here, we propose an approach to reduce the mentioned problems and obtain better results for the following processes in the applications of image analysis and computer vision.

The conventional approaches detect edges by thresholding gradient (magnitude) images. The gradient images are generally computed using simple operators, such as Sobel, Prewitt, and Roberts operators [6]. Even if the Canny detector [4] had been proven to be optimal for many types of edges, the edges are still obtained by globally thresholding the gradient image. In this kind of approaches, if the threshold value is too low, many edges are extracted accompanying with noises; if the threshold value is too high, fewer significant edges are remained. It is hard to acquire suitable edges and eliminate the noised or blurred influence in the one-scale gradient images.

Recently, many wavelet-based approaches have been proposed to acquire multiscale gradient images. Wavelet transform is a representation of signals in terms of basis functions which are obtained by dilating and translating a basic wavelet function. We can take a wavelet transform as a tool of low-pass and band-pass filters for edge detection and texture segmentation [3,5,7,12]. The wavelet transform has the properties of locality, multiresolution, compression, clustering, and persistence. These properties are suitable for most applications in image processing including edge detection. Mallat and Zhong [16] have implemented a multiresolution Canny edge detector with a wavelet

* Corresponding author. Tel.: +886 34227151x35202; fax: +886 3 422 2681.

E-mail address: tsengdc@ip.csie.ncu.edu.tw (D.-C. Tseng).

0262-8856/$ - see front matter
doi:10.1016/j.imavis.2004.11.005

transform. Beltrán et al. [2] used a neural network to classify the edge profile of different scales. Feng et al. [11] proposed an edge feature detection method for document images based on wavelet transform. Hsieh et al. [15] proposed a wavelet basis function following Canny's three criteria for edge detection.

Another kind of approaches to acquire edge information is tracking edges with graph-search methods. Van der Zwet and Reiber [20] proposed a graph-based gradient field transform method to search edges. Moon and De Jager [17] used an A*-algorithm to detect closed contours of apple images. Heijden [13] detected edges from noisy and/or blurred images. Falcão et al. [10] introduced an ultra-fast live-wire method to segment object boundaries. Usually, tracking only depends on the local property, it may extracts many improper or unnecessary edges for general images; thus tracking-based methods usually only deal with special images.

To extract edges with less noised or blurred cases and to reduce the broken edges and small fragments, we here combine a gradient-based edge detection and a wavelet-based multiscale edge tracking to extract edges as the system diagram shown in Fig. 1. The wavelet transform decomposes an image into different-scale and different-frequency subbands, and we produce multiscale shift-invariant gradient images from the high-frequency subbands. The proposed contextual-filter edge detector detects edges from the finest-scale gradient images; then, the edge tracker refines the detected edges on the multiscale gradient images.

The proposed approach has the following advantages. In edge detection, the noised or blurred cases are suppressed and the reliable edge points are detected. In edge tracking, we refine the detected edges and connect reasonable broken edges by exploring multiscale gradient images. The proposed approach can effectively reduce the noised or blurred influence and produces proper edges for the following applications.

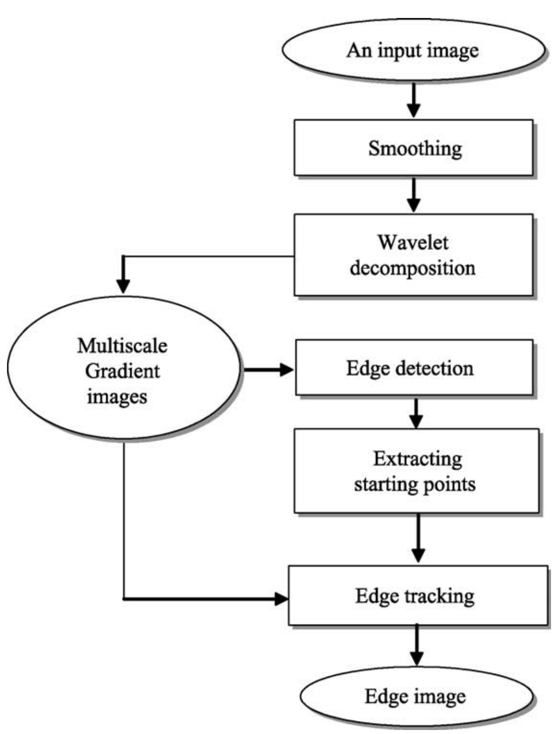

Fig. 1. The diagram of the proposed edge extraction approach.

The remaining sections of this paper are organized as follows. The generation of multiresolution shift-invariant gradient images using wavelet transform is proposed in Section 2. Section 3 presents the contextual filter for detecting edges. Section 4 describes the multiscale edge tracking. Experiments and comparisons on standard and medical images are described in Section 5. Finally, conclusions and discussions are given in Section 6.

2. The generation of multiresolution shift-invariant gradient images

The generation of multiresolution shift-invariant gradient images using wavelet transform is described in this section. Coifman and Donoho [8] had proposed an efficient full translation-invariant wavelet transform on a whole wavelet hierarchy for image denoise. The full translation-invariant wavelet transform is too complicated for generating multi-scale gradient images. We here use a simpler strategy coupled with the un-downsampling wavelet transform to generate multiscale shift-invariant gradient images.

2.1. Generation of shift-invariant gradient images

The discrete wavelet transform (DWT) is identical to a hierarchical subband system, where the subbands are logarithmically spaced in frequency. An image is firstly decomposed into four parts of low and high frequency subbands (i.e. LL_1, LH_1, HL_1, and HH_1) by cascading horizontal and vertical subsampled filters. The subbands labeled LH_1, HL_1, and HH_1 represent the finest-scale wavelet subbands consisting of wavelet coefficients. To obtain coarser-scale wavelet coefficients, the scaling subband LL_1 consisting of scaling coefficients is further decomposed and critically subsampled. This process can be repeated an arbitrary number of times which is determined by the application at hand. A layout of DWT subbands with three-scale dyadic decomposition of *Lena* image is shown in Fig. 2.

The (high-frequency) wavelet subbands describe the differences of neighboring pixels in an image. The larger wavelet coefficients indicate the boundary of two different intensity blocks in the original image. The LH_1, HL_1, and HH_1 coefficients describe the horizontal, vertical, and oblique edges of the image, respectively. There are two methods to generate a gradient image from the wavelet subbands. The first method uses the sum of squares of the corresponding coefficients in subbands LH_1 and HL_1 to generate the gradient image [16]; the second method takes the inverse DWT of all three wavelet subbands to generate