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Patch-based corner detection for cervical vertebrae in X-ray images

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ABSTRACT

Corners hold vital information about size, shape and morphology of a vertebra in an x-ray image, and recent literature (Al-Arif et al., 2015) [1,2] has shown promising performance for detecting vertebral corners using a Hough forest-based architecture. To provide spatial context, this method generates a set of 12 patches around a vertebra and uses a machine learning approach to predict corners of a vertebral body through a voting process. In this paper, we extend this framework in terms of patch generation and prediction methods. During patch generation, the square region of interest has been replaced with data-driven rectangular and trapezoidal region of interest which better aligns the patches to the vertebral body geometry, resulting in more discriminative feature vectors. The corner estimation or the prediction stage has been improved by utilising more efficient voting process using a single kernel density estimation. In addition, advanced and more complex feature vectors are introduced. We also present a thorough evaluation of the framework with different patch generation methods, forest training mechanisms and prediction methods. In order to compare the performance of this framework with a more general method, a novel multi-scale Harris corner detector-based approach is introduced that incorporates a spatial prior through a naive Bayes method. All these methods have been tested on a dataset of 90 X-ray images and achieved an average corner localization error of 2.01 mm, representing a 33% improvement in localization accuracy compared to the previous state-of-the-art method (Al-Arif et al., 2015) [2].[1]

1. Introduction

Evaluation of a cervical spine injury in an X-ray image is a major radiological challenge for an emergency physician. Studies show that 44% of cervical spine injuries are misdiagnosed due to misinterpretation [3] and up to 67% of patients with missed cervical fractures suffered neurological deterioration [4]. In order to decrease the risk of misinterpretation, automated image analysis algorithms can assist the emergency physicians. But applying these techniques on X-ray images has its own challenges due to low contrast, noise, and inter-patient variability.

In the past decade, researchers have tried to solve different problems on several radiographic mediums and body regions. A Hough transform-based method has been demonstrated in order to locate the vertebrae position, orientation and size in cervical X-ray images [5]. Another random forest based global spine localization algorithm has been presented in [6]. In [7], a 3D atlas-based method was proposed to locate the vertebra column in Computer Tomography (CT) scans. Dong et al. [8] utilized a probabilistic graphical model to measure the size and orientation and to identify cervical vertebrae on X-ray images. A layered framework of regression forest and hidden Markov model is proposed in [9] to localize vertebra centers in CT scans. Segmentation of the cervical vertebrae is addressed in [10–12]. The most popular techniques for segmentation are active shape models (ASM) and active appearance models (AAM) [11–16]. However, both ASM and AAM require a good initialization of the mean shape near the optimal segmentation. Corners can provide a good initialization for these models. In our previous work [1,2], we demonstrated a semi-automatic method to localize vertebra corners accurately using Hough forest [17]. In this paper, we extend this framework with new feature vectors, patch generation methods and prediction methods. Unlike [1,2] that uses a square region of interest (ROI), in this paper we explore rectangle and trapezoidal ROIs that better match vertebral geometry. A new prediction method is formulated which uses prior knowledge of patch classes known at test time due to the fixed manner in which patches are generated. Also unlike [1,2] that use multiple kernel density estimations (KDE) to aggregate votes coming from different leaf nodes, in this paper, a new method is implemented that

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collect all the votes together and use a single KDE, which improves both the accuracy and the computational efficiency. Apart from the basic intensity and gradient-based feature vectors, more complex and advanced feature vectors are investigated and compared against their usefulness in this framework. A novel Harris corner detector-based framework has also been formulated and implemented for comparison. All the methods are tested on a dataset of 90 emergency room X-ray images consisting of 450 vertebrae and 1800 corners, and show promising performance.

1.1. Contribution

The contribution of this paper is two-fold. First, the Hough forest framework has been improved. This has been achieved by introducing data-driven patch creation methods, a new cost-efficient single KDE based prediction method and a novel feature vector called random mirrored features (RMF). We have also presented a thorough evaluation of the framework over all the variants and achieved an average corner prediction error of 2.01 mm, greatly improving upon the previous state-of-the-art approach [2] that produced an average error of 3.03 mm on a challenging clinical dataset. Second, we have formulated a novel multi-scale Harris corner detector-based framework which requires only a fraction of a second for training and achieves comparative performance against our Hough forest framework.

2. Methodology

2.1. Data and manual annotations

90 lateral cervical spine X-ray images were collected from Royal Devon and Exeter Hospital in association with the University of Exeter. The age of the patients varied from 17 to 96. Different radiographic systems (Philips, Agfa, Kodak, GE) were used to produce the scans. Image resolution varied from 0.1 to 0.194 mm per pixel. The images include examples of vertebrae with fractures and degenerative changes. The data is anonymized and standard research protocols have been followed. For this work, 5 vertebrae C3-C7 are considered. Each of the 450 vertebrae from 90 images was manually annotated for corners and centers by an expert radiographer. Three annotated vertebrae are shown in Fig. 1.

2.2. Hough forest

2.2.1. Overview

Like other machine learning based frameworks, our Hough forest-based vertebral corner detection framework can be divided into two parts: training and testing; an overview is depicted graphically in Fig. 2. During training, the algorithm learns the relative position of the vertebral corners in relation with different patches generated from the vertebra. The patches are generated from a region of interest (ROI) around the vertebra. Three types of ROI geometry have been considered for evaluation (Section 2.2.2). These image patches are then converted into feature vectors. In this paper, we have evaluated performances of five different types of feature vectors including a novel feature vector named random mirrored feature (RMF) (Section 2.2.4). Training is performed by Hough forest where both classification and regression entropy are used together. This training scheme has also been compared against standard training schemes, i.e. using either classification or regression entropy (Section 2.2.3). The training process is summarized in Fig. 2a where all the options available for each stage are shown graphically. Once the forests are trained, the framework can be used to predict corners for the new vertebrae. At test time, a new image is provided with manually clicked vertebra centers. The ROIs are generated and patches are fed into trained forests, which then goes through a three stage process to localize corners: class prediction, filtering and corner estimation. The class prediction method has been improved by using prior knowledge from patch generation and corner estimation stage has been improved by using a cost efficient single kernel density estimation method (Section 2.2.5). The test time process is summarized as a flowchart in Fig. 2b.

2.2.2. Patch creation

The first step of the framework is to divide the vertebra into smaller patches. In order to do that, first, an ROI needs to be created around the vertebra centers. The position, overall size and orientation of this ROI can be calculated from the manually annotated vertebrae centers [1,2]. In previous work [1,2], a square ROI was constructed. However, distribution of the corners around the center for each vertebra reveals that vertebrae corners form a quadrilateral, that can be better approximated as a rectangle or trapezoid, as demonstrated in Fig. 3 which superimposes normalized corner distributions of the different cervical vertebral bodies in the dataset.

Based on this finding, rectangular and trapezoidal ROIs are introduced in this work. The size of the ROI is empirically computed from the distribution of the corners in the dataset. The trapezoidal ROI requires an affine transformation to warp the image whereas square and rectangle only need rotation. The affine transformation on a trapezoidal ROI results in an axis-aligned vertebral body (see Fig. 4b). The ROI is then divided in 16 equal-sized non-overlapping patches. Four center patches are discarded due to their homogeneous intensity distribution. Each of the boundary patches is associated with a class label (from 1 to 12) and five vectors. The class label (C_{patch}) represents the position of the patch within the ROI and 4 vectors ($\boldsymbol{d}_{1P1}$, $\boldsymbol{d}_{1P2}$, $\boldsymbol{d}_{1P3}$ and $\boldsymbol{d}_{1P4}$) point to four corners from the patch center and vector ($\boldsymbol{d}_2$) points to the vertebra center, as shown in Fig. 4. These image patches are converted to a feature vector (see Section 2.2.4) and fed into a Hough forest algorithm for training.

2.2.3. Training

Hough forest [17], a variant of the random forest [18,19] algorithm, has shown promising performance in object detection using votes from image patches. Here this algorithm has been adapted and customized in order to localize vertebral corners in X-ray images. In contrast to the random forest algorithm which performs either regression or classifica-

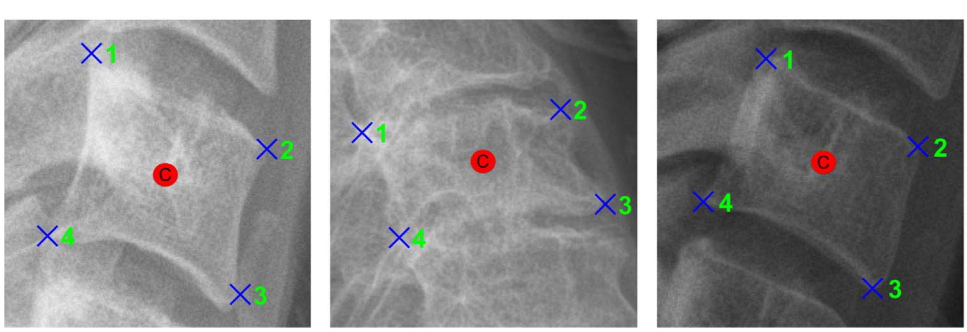

Fig. 1. Vertebra corners (x) and centers (o).