# Vertebrae Tracking in Lumbar Spinal Video-Fluoroscopy Using Particle Filters with Semi-Automatic Initialisation

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**Abstract.** Vertebrae tracking in lumbar spinal video-fluoroscopy is the first step in the analysis of vertebrae kinematic in patients with lower back pain. This paper presents a technique to track the vertebrae using particle filters with image gradient based likelihood measurement. In the first X-ray frame, the vertebrae are semi-automatically segmented and a bi-spline curve is fitted to the landmark points to construct the vertebrae outlines; then a particle filter is used to track the vertebrae through the sequence. The proposed technique is able to track the vertebrae in both lateral and frontal video-fluoroscopy sequences. The tracking results compare well with the ground truth data obtained by manually segmenting the vertebrae.

## 1 Introduction

Abnormal kinematic behaviour of the lumbar spine has been associated with low back pain [1, 2]. Intervertebral kinematic can provide useful diagnostic and follow up of back pain [3]. Hence the measurement of inter-vertebral motion has been investigated and many techniques have been developed to measure inter-vertebral motion [4] [3, 5] as well as many techniques to automatically segments the vertebrae [6–10]. Recording continuous spinal motion was first introduced by Breen et al. in [11]. This technique captures dynamic frames of spinal motion with low X-ray dosage than the normal single X-ray images [12]. In these X-ray videos the amount of radiation is such that the quality of a single image is much lower that of standard single X-rays. Although it is possible to see the similarities between vertebrae, there still a large variation in a single patient and between different patients.

Many researchers have focused on the segmentation of vertebrae and many techniques have been proposed to achieve better segmentation. Benjelloun et al. proposed a framework for vertebra segmentation using active shape models [13]. Statistical models are created after a training stage and the vertebrae are segmented using vertebrae detected contours. Lecron et al. also used active shape models and edge polygonal approximation to segment the vertebra in high resolution X-ray images. To speed up the segmentation, parts of their scheme were

processed on multi-CPU/multi-GPU architecture. Zhen et al. in [12] presented a Hough transform (HT) based technique to segment the vertebrae within an image sequence; where they used Fourier descriptors to describe the vertebral body shape. Klinder at al. presented a two-scale framework for the modelling and segmentation of the spine [14]. The global spine shape is expressed as a consecution of local vertebra coordinate systems while individual vertebrae are modelled as triangulated surface meshes.

The majority of These techniques were mainly applied to the segmentation/-tracking of vertebrae in lateral view sequences. In this paper we present more general tracking technique which is applied to both lateral and frontal video-fluoroscopy sequences. This technique uses few particle filters with an image gradient based likelihood measurement to track the vertebrae in parallel (i.e. each vertebra is tracked by a corresponding particle filter). The tracking is semi-automatically initialised as the user selects few land mark points in the first frame on which the detected edges are superposed.

The remainder of this paper is organised as follows. Section 2 briefly presents the particle filter used in this paper. Section 3 describes the vertebra model and the likelihood measurement based on image gradient and edge cues. The semi-automatic initialisation is described in Section 4. Section 5 presents the tracking results and compares them with ground truth data obtained but hand annotation. Finally, section 6 concludes the paper.

## 2 Particle Filters in Visual Tracking

Visual tracking is often formulated from a Bayesian perspective as a problem of estimating some degree of belief in the state $\boldsymbol{x}_t$ of an object at time $t$ given a previous observations $\boldsymbol{z}_{1:t}$ [15]. Bayesian filtering recursively computes a posterior density that can be written using Markov assumption:

$$p(\boldsymbol{x}_{t+1} \mid \boldsymbol{z}_{1:t+1}) \propto p(\boldsymbol{z}_{t+1} \mid \boldsymbol{x}_{t+1}) p(\boldsymbol{x}_{t+1} \mid \boldsymbol{z}_{1:t}) \tag{1}$$

Applying a Markov assumption, the prior density is the posterior density propagated from the previous time step using a dynamic model given by

$$p(\boldsymbol{x}_{t+1} \mid \boldsymbol{z}_{1:t}) = \int p(\boldsymbol{x}_{t+1} \mid \boldsymbol{x}_t) p(\boldsymbol{x}_t \mid \boldsymbol{z}_{1:t}) dx_t \tag{2}$$

The posterior in (1) cannot be computed analytically unless linear-Gaussian models are adopted. Isard and Blake suggested particle filtering for visual tracking in the form of Condensation [16] which is adopted in this paper. In Condensation, the posterior density $p(\boldsymbol{x}_t \mid \boldsymbol{z}_{1:t})$ is estimated at each time step $t$ by a set of $N$ particles $\{\boldsymbol{x}_t^n, w_t^n\}_{n=1}^N$ where each particle is a weighted random sample and $\sum_{n=1}^N w_t^n = 1$. The posterior is then

$$p(\boldsymbol{x}_{t+1} \mid \boldsymbol{z}_{1:t+1}) \propto p(\boldsymbol{z}_{t+1} \mid \boldsymbol{x}_{t+1}) \sum_{n=1}^{N} w_p^n p(\boldsymbol{x}_{t+1} \mid \boldsymbol{x}_t^n) \tag{3}$$

where the prior is now a mixture with N components. The Condensation involves (a) selecting the $n$th mixture component with probability $w_t^n$, (b) drawing a sample from it, and (c) assigning to the sample a weight proportional to its likelihood. Resampling is used to obtain samples with equal weights. The algorithm is given in Table 1. The dynamic (motion) model is encapsulated by the transition density $p(\boldsymbol{x}_{t+1} \mid \boldsymbol{x}_t^n)$. Typically, a sample can be drawn from it by adding random process noise and then applying deterministic dynamics (drift).

Table 1: Condensation Particle Filter

| |
|---|
| Draw samples $\boldsymbol{x}_{t+1}^n$ from $p(\boldsymbol{x}_{t+1} \mid \boldsymbol{x}_t^n)$ |
| Assign weights $w_{t+1}^n = p(\boldsymbol{z}_{t+1} \mid \boldsymbol{x}_{t+1}^n)$ |
| Normalise weights so that $\sum_{n=1}^{N} w_t^n = 1$ |
| Resample with replacement to obtain samples $\boldsymbol{x}_t^n$ |

## 3 Vertebrae Models

In order to apply the particle filters, both the state vector and the likelihood models have to be defined. As this research is about tracking different vertebrae viewed from two different angles, we adopt two distinct models for each vertebra. Benjelloun et al. used a local model and global model to segment cervical vertebrae from a single X-ray scan using active shape models [13]. Using global models is not possible in our case as the variation in the vertebrae shape in the lower spine is very large and single model would not be able to capture this variation. However since the vertebrae are moving in the image plane, the outline of each vertebra is expected to remain the same in each video-fluoroscopy sequence. Therefore, in this paper we adopt a rigid contour model for each vertebra in any given sequence. For the frontal view, a vertebra shape is represented by a closed contour; while for the lateral view the vertebra shape is represented by an open contour as show in the Fig. 1

Although the movement of the patient (i.e. that of the vertebrae) is controlled, the motion model of each vertebrae can only be estimated. This is due partially to the fact that the calibration is practically impossible as each patient is unique and also the inter-vertebrate motion is specific to each patient especially when there are abnormalities in the lumbar spine.

While the shape of a vertebrae is assumed to be invariant in each sequence, the position and the orientation do change. Hence the sate of a vertebra model at time $t$ is given by $e_t = (x_t; y_t; \theta_t)$; where $x_t$ and $y_t$ are the image coordinates of the contour centre and $\theta_t$ is the orientation relative to the centre of mass of the contour.

The likelihood measurement is based on the aggregation of intensity gradient information along each vertebra boundary. The gradient-based measurement $\psi(p)$ involves searching for maximum gradient magnitude points along short normal search line segments to the vertebrae model. In this paper, there are 100 such lines, each one is 7 pixels long. As the maximum gradient should be ideally

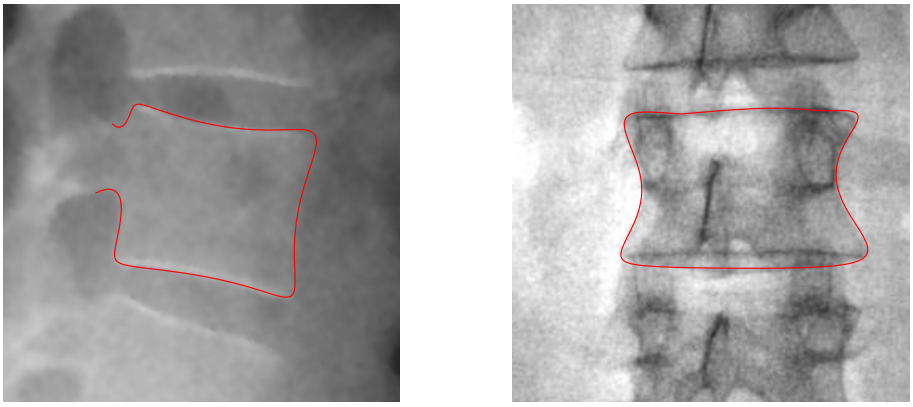
on the contour model, the distance between the maximum gradient point and the contour is used to penalise the contours which are further away from the maximum gradient. The gradient-based likelihood measurement $\psi(p)$ is given by

$$\psi(x_t^n) = \sum_{n=1}^{N} \frac{\mathrm{Max}_{i=1}^{M}\{\lambda_{i,n}\}}{1 + \eta D_n} \tag{4}$$

where N is the number of normal search line segments, $\lambda_{i,n}$ is the gradient at the $i$th point/pixel along the line $n$, $D_n$ is the Euclidian distance between the point with the maximum gradient and the vertebrae contour model, and $\eta$ is a weighing factor. In this paper the weighting factor is kept constant at $\eta = 0.1$ . Then likelihood is computed as follows

$$p(\boldsymbol{z}_t \mid \boldsymbol{x}_t^n) = \frac{\psi(\boldsymbol{x}_t^n)}{\sum_{n=1}^{N} \psi(\boldsymbol{x}_t^n)} \tag{5}$$

This likelihood should give a clear maximum in the correct location which corresponds to the model being aligned with maximum gradient.



(a) (b)

Fig. 1: Side view and frontal view of a Vertebrae: (a) Vertebra contour model in side view (b) Vertebra contour model in frontal view.

## 4 Semi-Automatic Initialisation

Tracking initialisation is an important step in any object tracking scheme. In this paper we adopt a semi-automatic approach where the user is guided by the detected edges in the first frame to specify few land mark points along the

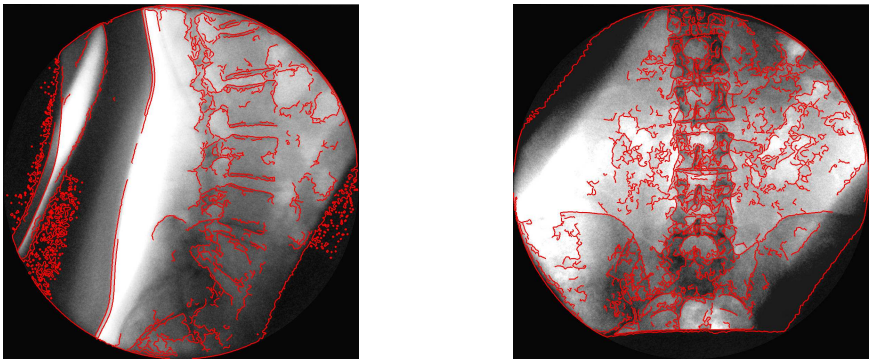


Fig. 2: Edge detected using Canny Edge detector.

vertebra outline. Canny edge detector is used to detect the edges in the first frame and these edges are superposed on the frame image. Since the X-rays are of law quality, the detected edges are very noisy as can be seen in figure 2. It is also clear from 2 that some edge curves appear to be aligned with vertebrae outlines; but some parts of the vertebrae outlines have no detected edge on them. In this paper, the user manually selects few land marks along the vertebra outline where no edge is detected and only selects a start and an end points on each edge curve which are considered to be aligned with vertebrae outlines. This edge segment then is automatically sampled, and sampled point are added to the manually selected landmarks to form the initial land mark sequence $S = [x_1, x_2, .., x_K; y_1, y_2, .., y_K]$ along the outline of the vertebra. Then a parametric spline is fitted to these points to form the vertebra contour model. Parametric splines are fitted independently to both $X = [x_1, x_2, .., x_K]$ and $Y = [y_1, y_2, .., y_K]$ using the parametric splines $x = f(t)$ and $y = g(t)$. The parametric splines would also help to filter out the out layers. Figure 1 shows the obtained vertebrae outline using the fitted spline.

## 5 Evaluation

### 5.1 Tracking Results

The proposed tracking method was implemented using a Gaussian transition density with a diagonal covariance matrix. Specifically, the variance parameters were $\sigma^2 = 25$ pixels for the vertebra model centre of gravity and $\sigma^2 = 4^o$ degree for the model rotation relative to the vertebra centre of gravity. In the sequences, the image size was resampled down to $870 \times 870$ pixels.

The proposed tracking technique is evaluated on two lumbar spinal video-fluoroscopy sequences of sagital and lateral flexions. **??** shows the tracking results for the side view with sagital flexion, while **??** shows the tracking results

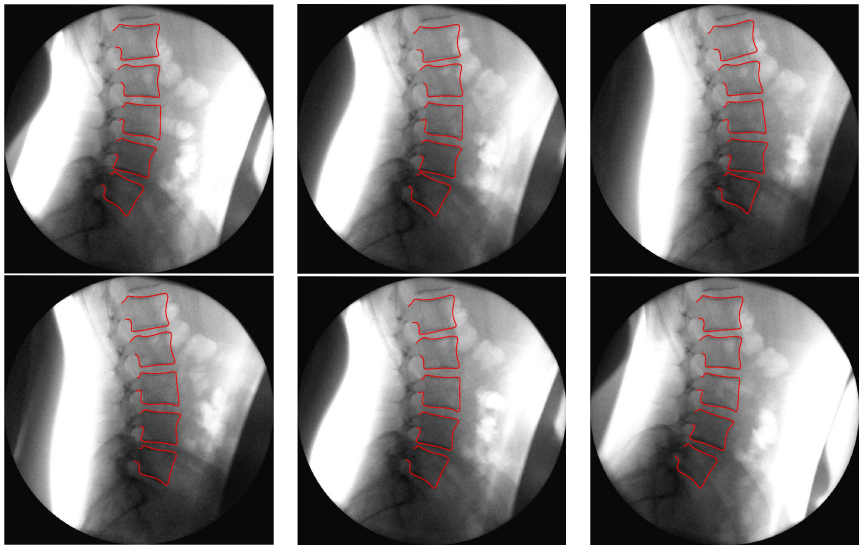


Fig. 3: Tracking results for the side view with sagital flexion: Frames 1, 40, 80, 120, 160, and 200

for the frontal view with lateral flexion. As we can see, the tracking was successful and all the vertebrae were correctly tracked throughout the sequences.

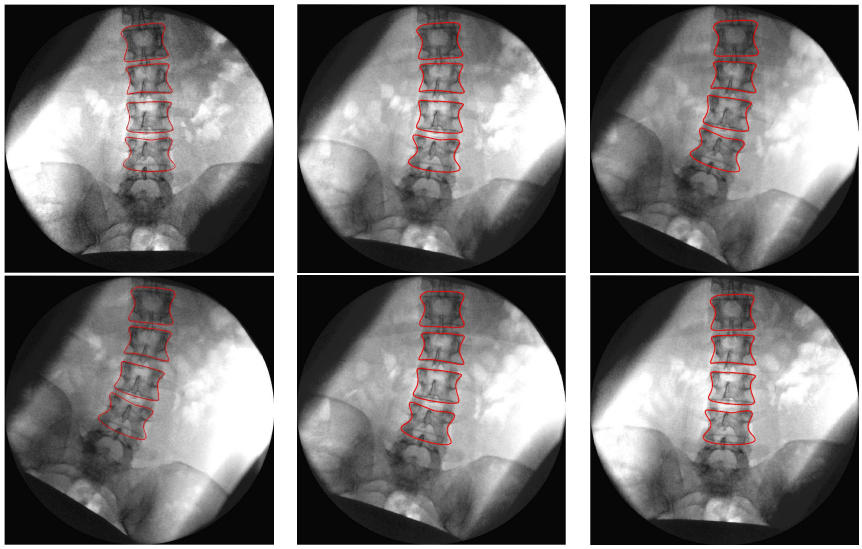


Fig. 4: Tracking results for the frontal view with lateral flexion to the right: Frames 1, 40, 80, 120, 160, and 200

### 5.2 Comparison With Ground Truth Data

To get some quantitative measurement of the quality of the tracking, we have manually annotated the vertebrae in the frames 150 from each sequence. Figure 4 shows the manually segmented vertebrae in blue and the tracked vertebrae in red. Although we did not get a perfect match, the overall tracking is very close to the segmented contours. The error here can be attributed to the segmentation in both the ground truth data and the initialisation stage of the tracker rather than the tracking technique.

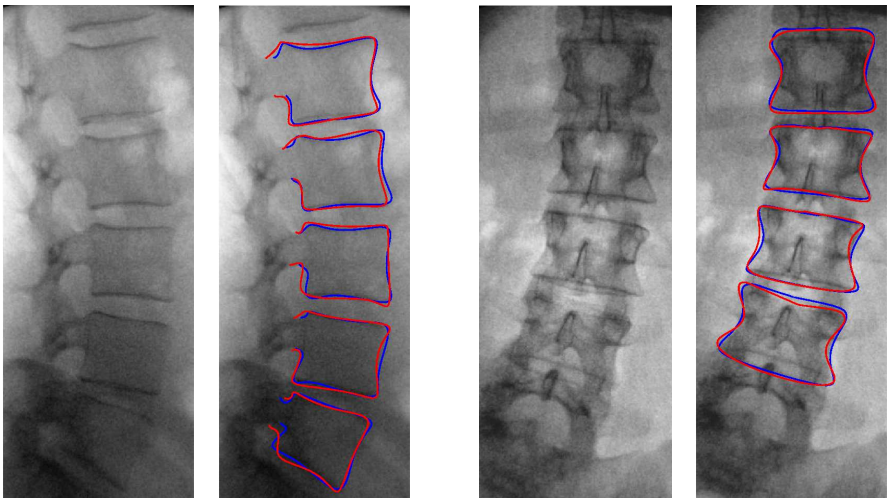


Fig. 5: The manually segmented vertebrae in blue and the tracked vertebrae in red in Frame 150 in both frontal and lateral views. Frames with no contours on are displayed for reference

## 6 Conclusion

A particle filter based technique for tracking vertebrae in lumbar spinal video-fluoroscopy has been proposed. In the first X-ray frame, the vertebrae are semi-automatically segmented and a bi-spline curve is fitted to the landmark points to construct the vertebrae outlines; then a particle filter is used to track the vertebrae through the sequence. The proposed technique was able to track the vertebrae in both lateral and frontal video-fluoroscopy sequences. Compared with the ground truth data obtained by manually segmenting the vertebrae in a given frame showed that the proposed technique would be a good starting point for vertebrae kinematic analysis in patients with lower back pain.

## References


1. Abbott, J.H., Fritz, J.M., McCane, B., Shultz, B., Herbison, P., Lyons, B., Stefanko, G., Walsh, R.M.: Lumbar segmental mobility disorders: comparison of two methods of defining abnormal displacement kinematics in a cohort of patients with non-specific mechanical low back pain. BMC Musculoskeletal Disorders **7** (2006) 45
2. Barrett, C.J., Singer, K.P., Day, R.: Assessment of combined movements of the lumbar spine in asymptomatic and low back pain subjects using a three-dimensional electromagnetic tracking system. Manual Therapy **4** (1999) 94–99
3. Holt, C.A., Evans, S.L., Dillon, D., Ahuja, A.S.: Three-dimensional measurement of intervertebral kinematics in vitro using optical motion analysis. Proceedings of the Institution of Mechanical Engineers Part H Journal of engineering in medicine **219** (2005) 393–399
4. Breen, A.C., Muggleton, J.M., Mellor, F.E.: An objective spinal motion imaging assessment (OSMIA): reliability, accuracy and exposure data. BMC Musculoskeletal Disorders **7** (2006) 1
5. Wong, K.W.N., Luk, K.D.K., Leong, J.C.Y., Wong, S.F., Wong, K.K.Y.: Continuous dynamic spinal motion analysis. Spine **31** (2006) 414–419
6. McCane, B., King, T.I., Abbott, J.H.: Calculating the 2D motion of lumbar vertebrae using splines. Journal of biomechanics **39** (2006) 2703–8
7. Reinartz, R., Platel, B., Boselie, T., Van Mameren, H., Van Santbrink, H., Romeny, B.T.H.: Cervical vertebrae tracking in video-fluoroscopy using the normalized gradient field. In Yang, G.Z., Hawkes, D., Rueckert, D., Noble, A., Taylor, C., eds.: International Conference on Medical Image Computing and ComputerAssisted Intervention MICCAI. Volume 12 of Lecture Notes in Computer Science., Springer (2009) 524–531
8. Wong, A., Mishra, A., Fieguth, P., Clausi, D., Dunk, N.M., Callaghan, J.P.: Shape-guided active contour based segmentation and tracking of lumbar vertebrae in video fluoroscopy using complex wavelets. Conference Proceedings of the International Conference of IEEE Engineering in Medicine and Biology Society **2008** (2008) 863–866
9. Ma, J., Lu, L., Zhan, Y., Zhou, X., Salganicoff, M., Krishnan, A.: Hierarchical segmentation and identification of thoracic vertebra using learning-based edge detection and coarse-to-fine deformable model. Medical Image Computing and Computer-Assisted Intervention **13** (2010) 19–27
10. Zamora, G., Sari-Sarraf, H., Long, L.R.: Hierarchical segmentation of vertebrae from x-ray images. Medical Imaging 2003 Image Processing **5032** (2003) 631–642
11. Breen, A.: A computer/x-ray method for measuring spinal segmental movement: a feasibility study. 2nd Annual Conference on Research and Education of the Pacific Consortium for Chiropractic Research (1987) 13–14
12. Zheng, Y., Nixon, M.S., Allen, R.: Automatic Segmentation of Lumbar Vertebrae in Digital Videofluoroscopic Imaging. IEEE Transactions on Medical Imaging **23** (2004) 45–52
13. Benjelloun, M., Mahmoudi, S., Lecron, F.: A framework of vertebra segmentation using the active shape model-based approach. International Journal of Biomedical Imaging **2011** (2011) 621905
14. Klinder, T., Wolz, R., Lorenz, C., Franz, A., Ostermann, J.: Spine segmentation using articulated shape models. Medical Image Computing and Computer-Assisted Intervention **11** (2008) 227–234

15. McKenna, S.J., Nait-Charif, H.: Tracking human motion using auxiliary particle filters and iterated likelihood weighting. Image and Vision Computing **25** (2007) 852–862
16. Isard, M., Blake, A.: ICondensation: Unifying low-level and high-level tracking in a stochastic framework. In: Proceedings of the 5th European Conference on Computer Vision. Volume 1. (1998) 893–908