JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

3D Reconstruction of Leg Bones from X-Ray Images using CNN-based Feature Analysis

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Abstract: The problem of 3D reconstruction of subject-specific bones from X-ray scans is crucial in several medical applications, such as diagnosis. Using feature analysis, we offer a method for rebuilding 3D leg bones from 2D X-Ray images. However, bounding boxes are identified using Convolutional Neural Networks (CNN). They are employed to extract feature ellipses and points. These qualities match the feature data of the 3D bone model. The aligned border of the 3D model is then used to determine the X-ray boundary. To optimize the 3D model, apply the statistical shape model parameter. For planning surgeries or making diagnoses, three-dimensional (3D) models of the human anatomy have been available for a while. While reconstructing the 3D module, the various picture modalities often rely on a series of sequential two-dimensional (2D) scans. Therefore, such purchases are costly, time-consuming, and frequently expose the patient to too much radiation. Due to this, studies have been presented in recent years that infer 3D anatomical elements from 2D tests like x-rays for implant templating in total knee or hip arthroplasty. The current study demonstrated a novel deep learning-based method for reconstructing 3D medical picture volumes from a single x-ray image.

***Index Terms* - 2-D to 3-D, CNN, x-ray images**

I. INTRODUCTION

The present reconstruction methods from X-ray images can be classified into six types. This classification and the information presented below complement the literature analysis.

- Point-based methods: This class's methods are based on locating and matching points and other low-level primitives in multi-view radiography. The two primary categories of 3D reconstruction point-based approaches are Stereo Corresponding Point (SCP) based Approaches and Non-Stereo Corresponding Point (NSCP) based Techniques. While the NSCP approach does not call for correlation between images taken at specific locations, the SCP technique does. These techniques heavily rely on the skilled operator's capacity to identify precise locations. As a result, they are difficult to repeat. Due to the manual recognition, these approaches take 2 to 4 hours to rebuild.
- Contour-based Methods: The goal of these techniques is to link recognizable 2D contours from radiography to 3D lines visible on the surface of a reference object. Then, using several images, a deformation of an elastic 3D model about 2D contours is carried out [2]. Contrary to point-based methods, contour-based procedures make use of a higher level of geometric primitives, which avoids the challenge of locating complementary points and minimizes the need for human intervention. 3D Reconstruction of Leg Bones from X-Ray Images using CNN-based Feature Analysis. Although contour-based methods have adequate accuracy, 3D reconstruction for these methods requires a lot of time. The time needed for this 3D reconstruction procedure for lower limbs was predicted to be between 15 and 35 minutes.

- Statistical Shape Modelling-based Methods: Another approach for reconstructing 3D forms uses statistical modeling and shape analysis [4], [5]. This method only needs a few sparse landmark vertices on the surface of the bone. Since the knowledge of those few landmark vertices is insufficient for a complete 3D surface reconstruction, prior information is necessary. A collection of training surfaces that depict accurate changes to the surface of interest can be used to build a statistical model. The subject's anatomy is then matched using the statistical model and landmark vertices learned from radiographs as prior information. In conclusion, a full and reasonably realistic 3D anatomical surface is inferred from a sparse or incomplete collection of 3D vertices using the statistical shape model-based technique. Model-based methods are generally trustworthy due to their ability to correctly depict structures, with reported reconstruction errors of 1-3 mm.

- Parametric Methods: Statisticians do not employ the entire set of points identified by SSM modeling, but rather anatomical descriptive parameters (DP) generated from the area of interest [6]. These methods are excellent for producing a first 3D reconstruction that is both rapid and stable. These techniques produce a generalized parametric model for the representation of the object of interest. According to the considered bone structure, this extended parametric model incorporates many geometric primitives such as points, lines, circles, and spheres.

- Hybrid Methods: A series of reconstruction models that combine several different types of reconstruction models are referred to as hybrid approaches. The methods in this class will have a variety of features depending on how they are combined and used. One illustration is the integration of statistical and image-based biplanar reconstruction techniques.

- Deep Learning Methods: Recently, deep learning algorithms have been utilized to reconstruct the shape of a particular item from a large number of images. A three-dimensional surface can be geometrically recreated by triangulating two or more images and assuming the cameras' positions were taken near one another.

II. LITERATURE SURVEY

1. According to [2] without the requirement for a manually segmented database, they may properly train a CNN on the digitally reconstructed radiographs (DRR) of a 3D articulating form model of the item of interest. The articulating model guarantees that the bones of interest in the DRR have a realistic look, giving good training data for segmentation. We train a CNN on DRRs to segment the phalanges of a horse limb from radiographs as a proof-of-concept and demonstrate that it outperforms a geodesic active contour segmentation approach in this context. Our suggested training technique is successful for articulating objects, and they may subsequently use the resultant CNN to perform real-data segmentation tasks provided
2. According to [2] They created a method for directly reconstructing the 3D shape of the knee bones from two bi-planar X-ray pictures using a Convolutional Neural Network (CNN) from beginning to end. For surgical planning, implant fitting, and postoperative evaluation in the clinic, 3D models of the bones must be taken. X-ray imaging exposes patients to significantly less ionizing radiation than Computer Tomography (CT) imaging while being much more widely used and less expensive than Magnetic Resonance Imaging (MRI) scanners. On the other hand, recovering 3D models from such 2D photos is exceedingly challenging. Instead of using the conventional method of statistically modeling the shape of each bone, our deep network learns the distribution of the bones' shapes straight from the training images. To switch between the X-Ray and DRR modalities, we use style transfer
3. According to [3] a deep learning network for predicting, and building very accurate 3D bone models directly from X-ray scans The study included 105 actual X-ray images of a healthy wrist joint and a total of 173 computed tomography (CT) images. To make up for the dataset's small size, digitally reconstructed radiography (DRR) images made from CT were used as training data instead of actual X-ray images. The test's actual X-ray images were converted into DRR-like images, which were then fitted to the network to produce a high-accuracy 3D bone model estimate from a small amount of data.

Sr no	Name of paper	Published year	Description
1	2D–3D reconstruction of distal forearm bone from actual X-ray images of the wrist using convolutional neural networks.	2021	It describes a method for reconstructing 3D bone models of the distal forearm from 2D X-ray images using convolutional neural networks (CNNs). The authors use a dataset of X-ray images and corresponding CT scans to train a CNN to predict the 3D bone shape from the X-ray images. They evaluate the method using both synthetic and actual X-ray images and show that it can produce accurate 3D bone models with low error compared to ground truth CT scans. The method has potential applications in orthopedics, where accurate 3D bone models can aid in surgical planning and patient-specific implants. The authors suggest that the method could be extended to other bones and medical imaging modalities.
2	End-To-End Convolutional Neural Network for 3D Reconstruction of Knee Bones From Bi-Planar X-Ray Images	2020	describes a method for reconstructing 3D knee bone models from bi-planar X-ray images using an end-to-end convolutional neural network (CNN). The authors use a dataset of X-ray images and corresponding CT scans to train a CNN to predict the 3D bone shape from the X-ray images. They evaluate the method using both synthetic and actual X-ray images and show that it can produce accurate 3D bone models with low error compared to ground truth CT scans. The authors suggest that the method could be used in clinical settings to aid in surgical planning and implant design. They also propose that the method could be extended to other joints and medical
3	2D-to-3D: A Review for Computational 3D Image Reconstruction from X-ray Images	2022	provides a comprehensive overview of computational 3D image reconstruction techniques from X-ray images. The authors discuss various methods including model-based, feature-based, and learning-based approaches. They highlight the advantages and limitations of each method and compare their performance in terms of accuracy, efficiency, and generalizability. The authors also discuss the challenges and future directions in this field, including the need for large annotated datasets and the integration of multiple modalities. The review paper provides a valuable resource for researchers and practitioners interested in computational 3D image reconstruction from X-ray images

4	3D Reconstruction from Multi-View Medical X-Ray Images – Review and Evaluation of Existing Methods	2015	It provides a review and evaluation of existing methods for 3D reconstruction from multi-view medical X-ray images. The authors discuss various approaches for multi-view X-ray image acquisition and the challenges associated with 3D reconstruction from X-ray images. They review and evaluate different methods for 3D reconstruction, including model-based, feature-based, and learning-based approaches. The authors provide a comparison of the methods in terms of their accuracy, computational efficiency, and limitations. They also highlight the potential applications of 3D reconstruction from X-ray images in clinical settings. The review paper provides a useful resource for researchers and practitioners interested in 3D reconstruction from multi-view medical X-ray images
5	3D Reconstruction of 2D X-Ray Images	2019	It presents a method for reconstructing 3D images from 2D X-ray images. The authors discuss the challenges associated with 3D reconstruction from 2D images, including the lack of depth information and the presence of noise and artifacts in the images. They propose a method based on a combination of feature-based and model-based approaches, which uses a genetic algorithm to optimize the parameters of a 3D model. The authors evaluate the method using both synthetic and real X-ray images and compare the results with ground-truth CT scans. They show that their method can produce accurate 3D models with low error compared to the ground truth. The authors suggest that their method has potential applications in medical imaging and computer

III. PROPOSED METHODOLOGY:

CNN: Convolutional Neural Networks (CNN), are deep neural networks used to process data that have a grid-like topology, e.g images that can be represented as a 2-D array of pixels. A CNN model consists of four main operations: Convolution, Non-Linearity (Relu), Pooling, and Classification (Fully-connected layer).

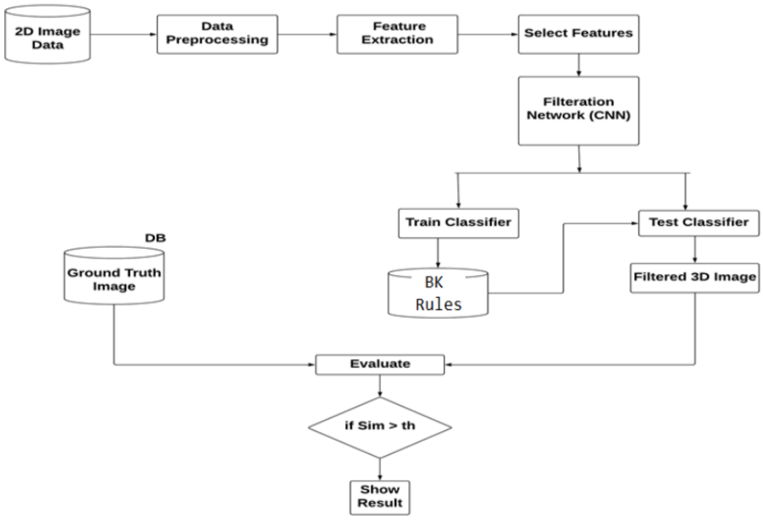
1. Convolution: The purpose of convolution is to extract features from the input image. It preserves the spatial relationship between pixels by learning image features using
small squares of input data. It is usually followed by Relu.
2. Relu: It is an element-wise operation that replaces all negative pixel values in the feature map with zero. Its purpose is to introduce non-linearity in a convolution network.
3. Pooling: Pooling (also called downsampling) reduces the dimensionality of each feature map but retains important data.
4. Fully-connected layer: It is a multi-layer perceptron that uses the SoftMax function in the output layer. Its purpose is to use features from previous layers for classifying the input image into various classes based on training data.

The combination of these layers is used to create a CNN model. The last layer is fully connected. A convolutional neural network (CNN) consists of many neural network layers. Two different types of layers, convolutional and pooling, are typically alternated. The depth of each filter increases from left to right in the network. The last stage is typically made of one or more fully connected layers.

IV. SYSTEM ARCHITECTURE

In this work, we present a technique for reconstructing 3D leg bones from 2D X-Ray pictures. Convolutional Neural Networks are used to identify bounding boxes first (CNN). They are used to extract feature points and feature ellipses. These characteristics correspond to the 3D bone model's feature information. The X-Ray boundary is then identified from the 3D model's aligned border. The Statistical Shape Model parameter is used to fine-tune the 3D model. By collecting feature information from X-Ray pictures using CNN and performing alignment and SSM fitting, we present a better technique for the 3D reconstruction of leg bones in X-Ray images. Boundaries are identified using feature ellipses as well as feature points in regions where boundary outlines are difficult to extract.

Detecting feature points and feature ellipses using CNN that can identify bounding boxes unifies feature information detection.



V. CONCLUSION AND FUTURE SCOPE

In ”3D Modeling”, we have presented a probabilistic framework for matching two sets of features, extracted automatically from images, which takes into consideration the global structure of the feature sets. Medical uses, such as diagnosis and 3D reconstruction of subject-specific bones from X-ray data, are a major issue. Using feature analysis, we offer a strategy for recreating 3D leg bones from 2D X-Ray images. Bounding boxes are initially identified using Convolutional Neural Networks (CNN). An improved approach for 3D reconstruction of leg bones in X-ray images uses CNN and SSM fits to align information. The normalization procedure is used to obtain a doubly stochastic matrix denoting the probabilities of a match for the two feature sets. The method works by minimizing the probability of a mismatch between the shapes of the features, after taking into account their spatial arrangement. Robustness is achieved by including prior information regarding these feature sets. We emphasize that the prior can be easily obtained from video, and needs to be computed only once for a class of objects. A user-friendly interaction environment is provided to facilitate a novice user to convert the 2D image to a 3D object.

VI. ACKNOWLEDGMENT

We would like to thank our guide, Prof. Sachin Pande, for helping us choose the topic, for providing an opportunity to work on this project, and for guiding us.

We are grateful to our reviewers Prof Anant Bagade and Prof. Vinit Tribhuvan who provided the necessary feedback.

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