

# Joint Track Machine Learning

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# Outline

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## Introduction

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## Acknowledgments

I would like to thank the McJunkin Family Charitable Foundation for their generous grant that supports this work.

## Motivation

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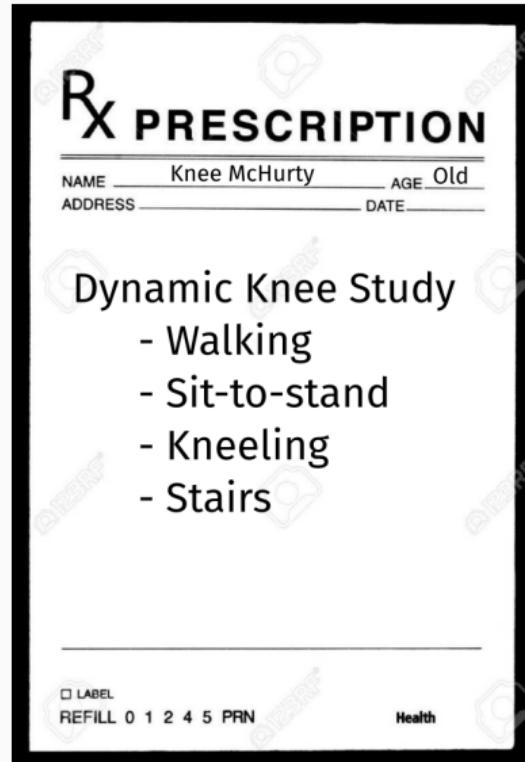
# The Problem

- 20% of patients receiving TKA are dissatisfied.
  - Instability, pain, unnatural [1, 3, 17].
- No reliable method of clinically assessing and quantifying joint dynamics.
  - Too much human supervision, too time consuming



# Our Proposition

Orthopaedic surgeons and clinicians would readily adopt a practical and inexpensive technology that allows them to measure a patient's knee kinematics during activities of daily living.



# Constraints

- It must fit within a standard clinical workflow
- The technology must utilize equipment commonly found in hospitals
- There must not be significant human supervision nor interaction to generate an examination report.



## Background

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# Rigid Body Transformations

## Translation

$$\begin{pmatrix} v'_x \\ v'_y \end{pmatrix} = \begin{pmatrix} v_x \\ v_y \end{pmatrix} + \begin{pmatrix} t_x \\ t_y \end{pmatrix}$$

→

$$\begin{pmatrix} v'_x \\ v'_y \\ 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} v_x \\ v_y \\ 1 \end{pmatrix}$$

# Rigid Body Transformations

## Rotations

$$R_x = \begin{pmatrix} 1 & 0 & 0 \\ 0 & c_x & -s_x \\ 0 & s_x & c_x \end{pmatrix}$$

$$R_y = \begin{pmatrix} s_y & 0 & c_y \\ 0 & 1 & 0 \\ c_y & 0 & -s_y \end{pmatrix}$$

$$R_z = \begin{pmatrix} c_z & -s_z & 0 \\ s_z & c_z & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

# Rigid Body Transformations

## Homogeneous Transformation Matrices

$$\begin{aligned}\tilde{\vec{v}}' &= \begin{pmatrix} R_{3 \times 3} & \vec{t}_{3 \times 1} \\ 0 & 0 & 0 & 1 \end{pmatrix} \tilde{\vec{v}} \\ &= T_B^A \tilde{\vec{v}}\end{aligned}$$

Now we have a notation that allows us to describe arbitrary movement between reference frames.

# Projective Geometry

$$\begin{pmatrix} x_s \\ y_s \\ z_s \\ 1 \end{pmatrix}_i = T_{\text{scene}}^{\text{cam}} \tilde{p}_i^{\text{obj}}$$

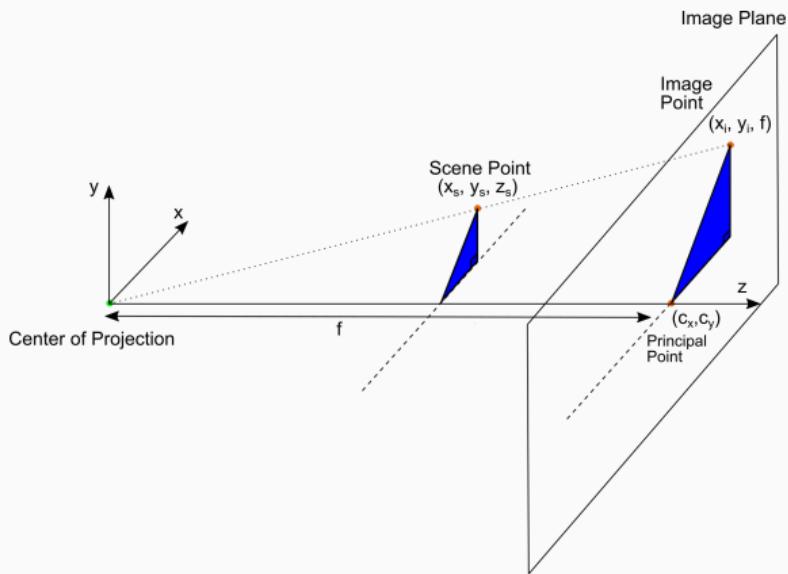
$$\begin{pmatrix} \tilde{x}_{\text{img}} \\ \tilde{y}_{\text{img}} \\ \tilde{z} \end{pmatrix} = \begin{pmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{pmatrix} \vec{x}_s$$

Where

$$x_{\text{img}} = \frac{\tilde{x}_{\text{img}}}{\tilde{z}} = \frac{f}{z_s} x_s$$

$$y_{\text{img}} = \frac{\tilde{y}_{\text{img}}}{\tilde{z}} = \frac{f}{z_s} y_s$$

Note: We are still in the camera's reference frame



## Pixel Coordinates

Convert camera coordinates into image coordinates.

$$p_x = k_x x_{img} + c_x$$

$$p_y = k_y y_{img} + c_y$$

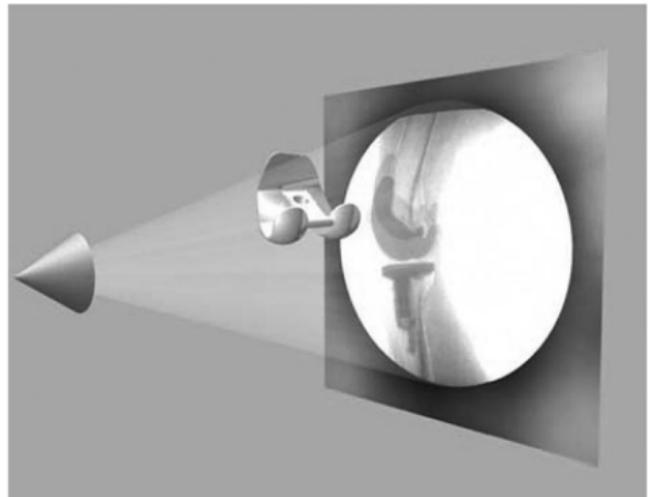
Where

$k \equiv$  Pixel Spacing

$c \equiv$  Image Focal Point

## Model-Image Registration

If we know the projective parameters of the fluoroscopy machine, can we tinker with  $T_{implant}^{cam}$  so that our virtual projection matches the fluoroscopic image?



From [15]

## Historical Methods

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## Overview

Many different approaches have attempted to solve the model-image registration problem.

- Pre-computed projections
- Skin-mounted motion Capture
- Biplane Imaging
- Iterative Projections
- Model-based Roentgen Stereophotogrammetry

# Pre-Computed Projections

- Saving space and memory by pre-computing as much as possible.
- Pre-computed distance maps [21, 13].
- Pre-computed shape libraries [2]

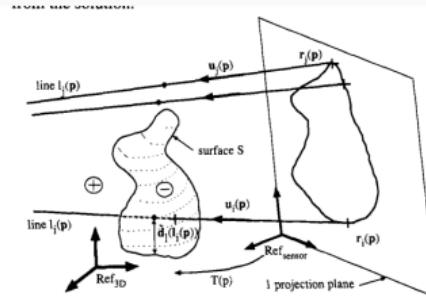
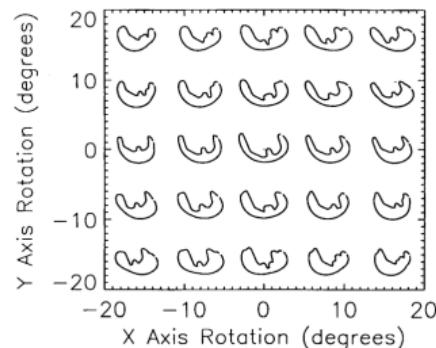


Fig. 2. Projection line to surface distance computation.

From [13]

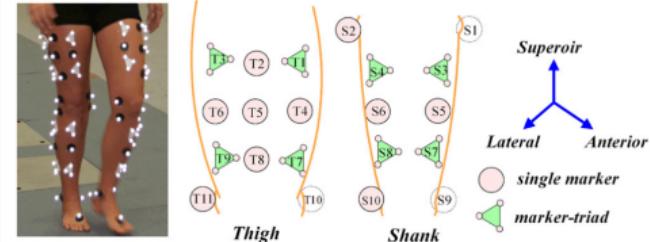


From [2]

## Limitations of Pre-Computed Projections

- Requires an accurate contour from the input image in order to perform calculations.
  - Human supervision vs. inaccuracy.

# Motion Capture (MoCap)



From [8]

- Can measure motion of MoCap beads very accurately.
- Skin-mounted [8, 11, 14].
- Bone pins [12] (any volunteers?).



From [12]

# Limitations of Motion Capture

## Skin Mounted

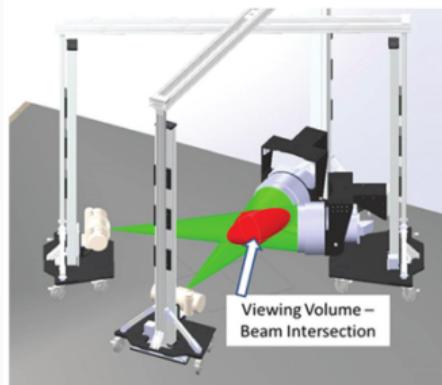
- Doesn't accurately describe underlying skeletal motion with clinical accuracy [8, 11, 14].

## Bone Pins

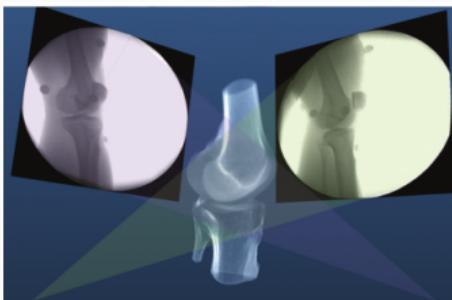
- Bone Pins
- Need I say more?

# Biplane Imaging

- Utilizes multiple cameras to resolve 3D position and orientation[9, 5].
  - Highly accurate.
  - Gold Standard.



Both from [9]

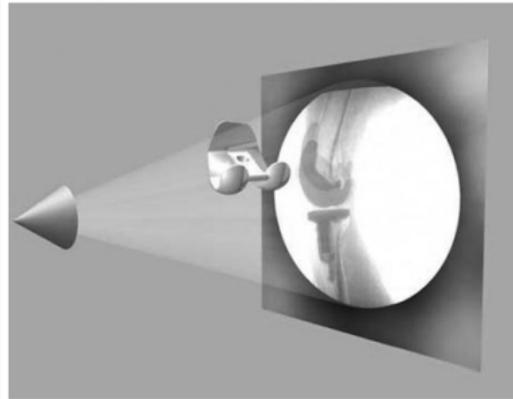


## Limitations of Biplane Imaging

- Not many hospitals have biplane fluoroscopy setups.
- Clinically impractical

# Iterative Projections

- Take advantage of modern computational graphics pipelines to quickly perform projection matching.
  - Image/Intensity similarity metrics [15]
  - Feature/Contour similarity metrics [7]



From [15]



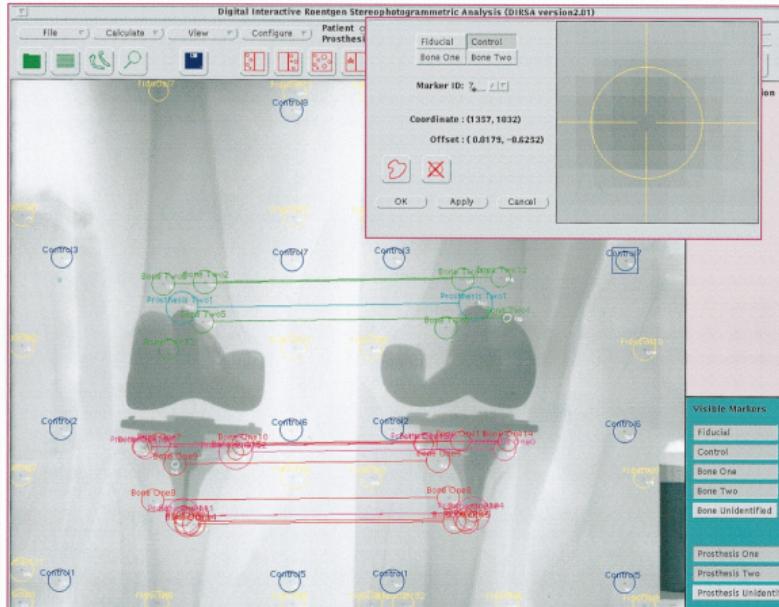
From [7]

## Limitations of (historic) Iterative Projection Methods

- Requires human supervision for:
  - Pose initialization
  - Escaping local minima
  - Implant detection
- Chaotic and Noisy objective function

# Model-based Roentgen Stereophotogrammetry (MBRSA)

- Uses implanted tantalum beads for motion tracking [19, 18]
- Extremely accurate [10, 16]
- Gold standard Measurement [4]



From [19]

## Limitations of MBRSA

- Involves additional surgical procedures for inserting tantalum beads
- Human supervision
- Typically requires bi-plane imaging.

## Aims page

Aims

# Aims

## Aims 1/2

Joint Track Machine

Learning and Overcoming

Single-Plane Limitations

## Aim 3/4

Pilot Trials and

Standardized Kinematics

Exam

## Aim 5

Joint Track Auto Toolkit

## **Aim 1 - Joint Track Machine Learning**

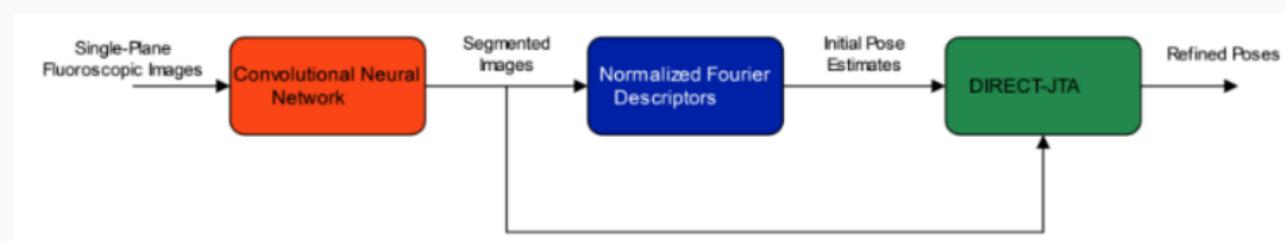
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# Goal

Demonstrate the feasibility of a fully autonomous, model-image registration pipeline.

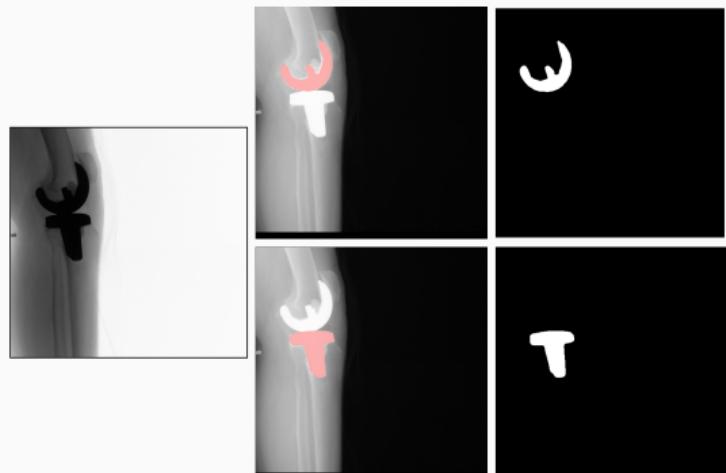
# Method

- Three-tiered approach
  - Convolutional Neural networks (CNN) for autonomous implant detection
  - Normalized Fourier Descriptor shape libraries
  - Robust contour-based global optimization scheme



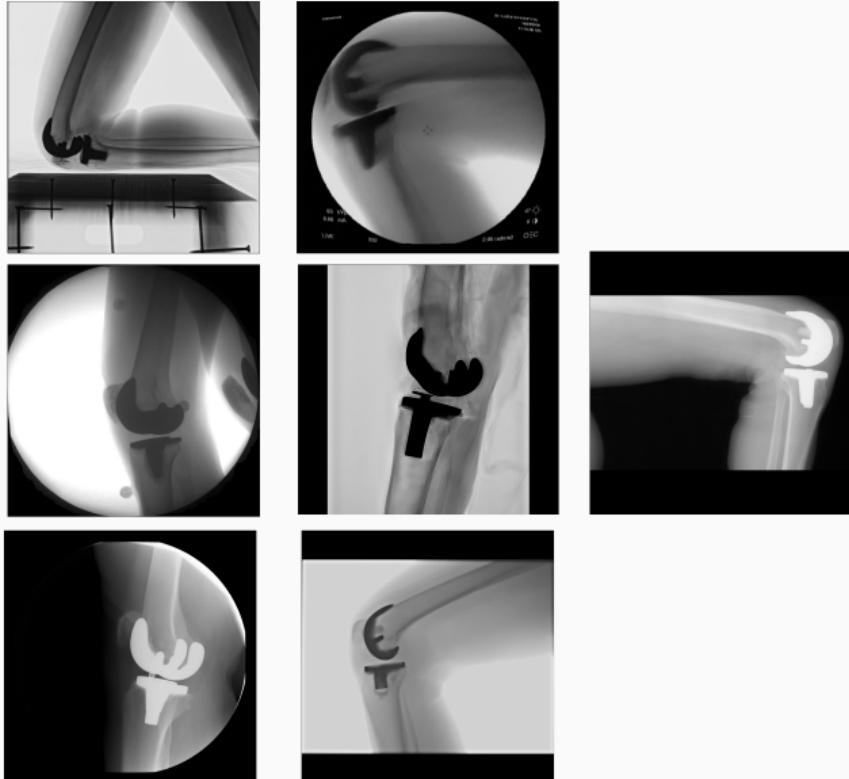
# Autonomous Implant Detection Using Convolutional Neural Networks

- 2 CNNs
  - Femoral and Tibial implants
- High Resolution Network [20]



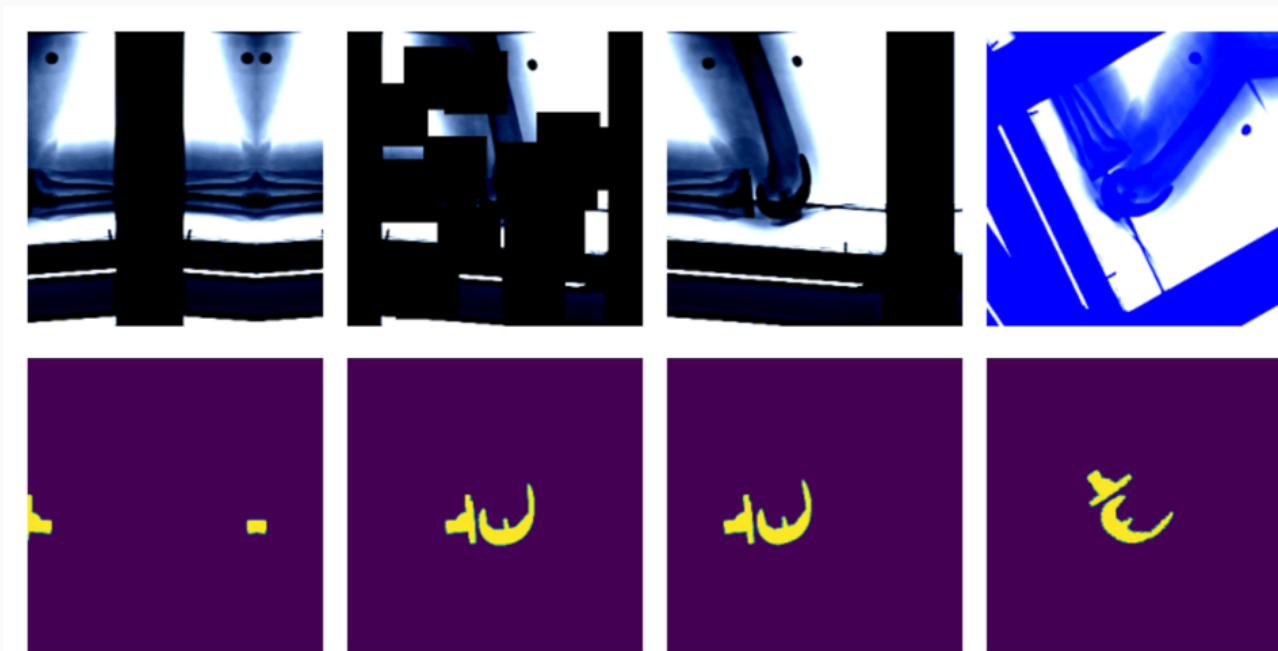
# Neural Network Data

- ~8000 images
  - 7 TKA kinematics studies
  - PUT DATA INFO HERE!!!!



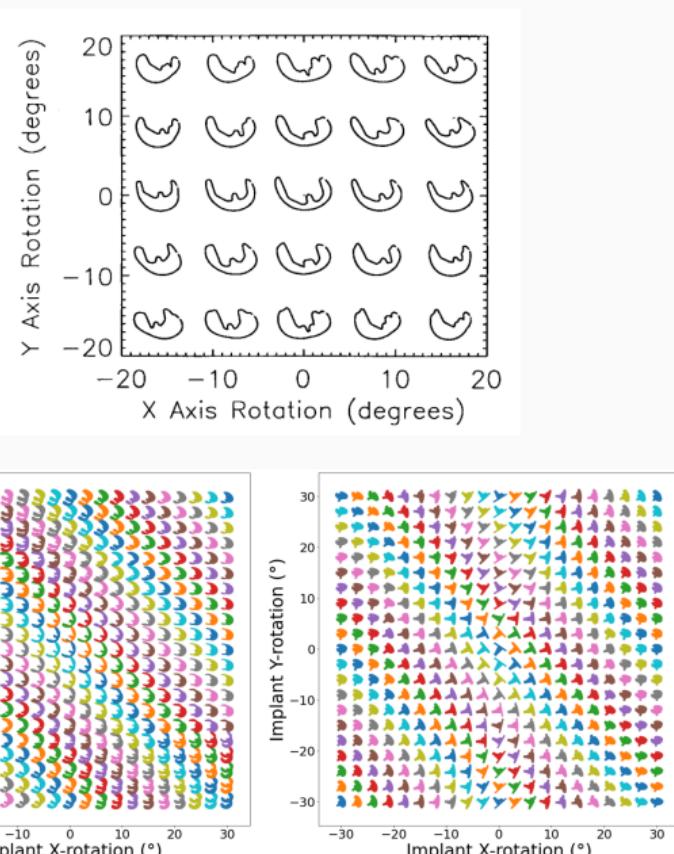
# Neural Network Robustness

- Additional augmentations introduced during training [6].



# Normalized Fourier Descriptor Shape Libraries

- Pose initialization using segmentation output.
- $\pm 30^\circ$  library span at  $3^\circ$  increments.



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