# Real-time Gymnast Detection and Performance Analysis With a Portable 3D Camera

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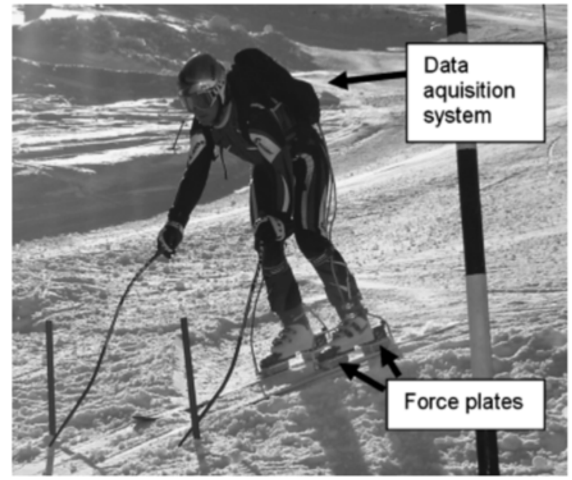
# Need for Performance Analysis

- Need quantitative data, related to performance
- Traditional methods – force plates, motion capture systems




Alpine skiing [1]

Cycling [2]

- Problem: can't use force plates and markers while competing
- Need low cost system, easy to set up for non technical users

# Pommel Horse Gymnastics Event

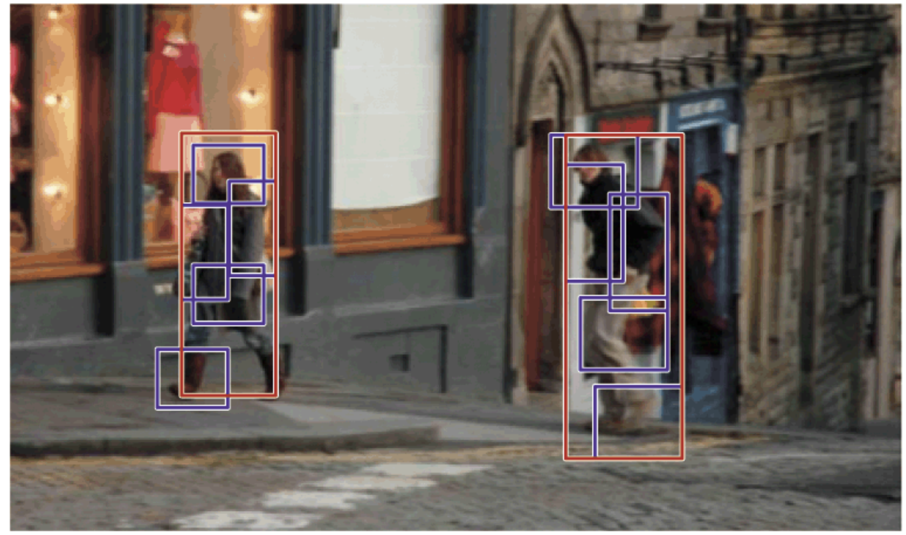

*Sam Mikulak - Pommel Horse - 2012 Visa Championships - Sr. Men [3]* https://www.youtube.com/watch?v=19N6uruAyos

# Portable 3D Camera

- New developments in depth 3D cameras
- New opportunities – low cost portable, accurate
- Kinect 2.0 specs:
  - Time of flight sensor
  - 512x424 depth image, 30 fps
  - 0.5-4.5 m

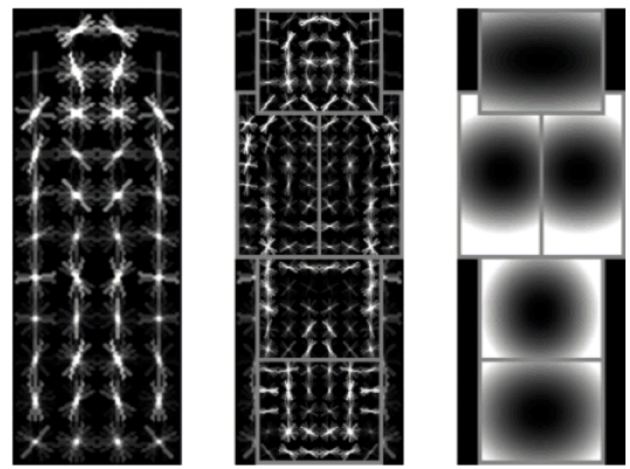
https://www.youtube.com/watch?v=9YVmB0AIrvw

# Human Detection



- Histograms of oriented gradients (HOG)
  - Descriptor composed of HOG cells
  - Sliding window
  - SVM classifier
  - Extended to part-based models

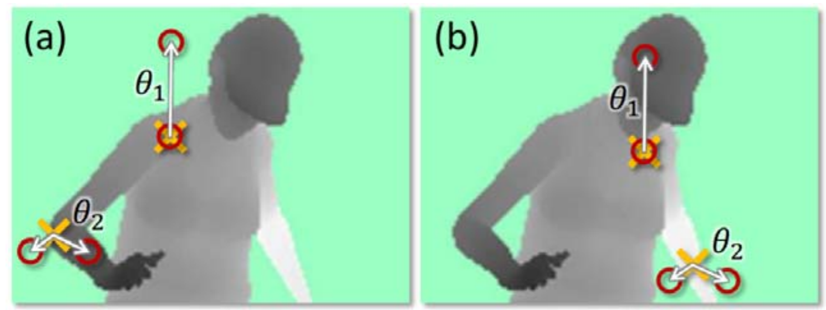
- Problem:  Trained for typical upright body poses

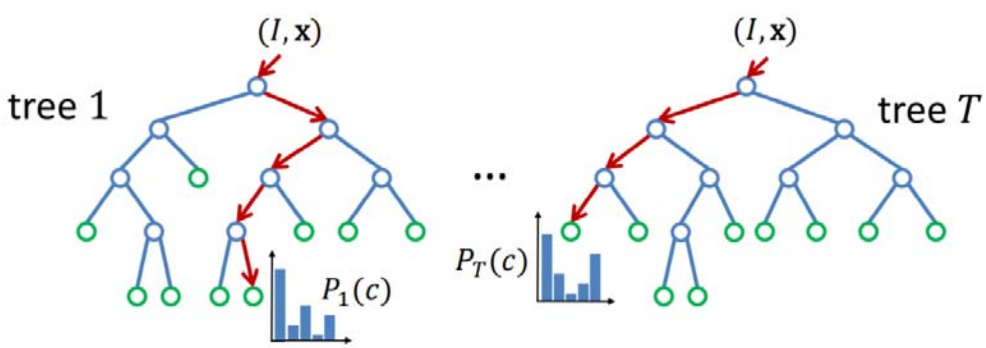


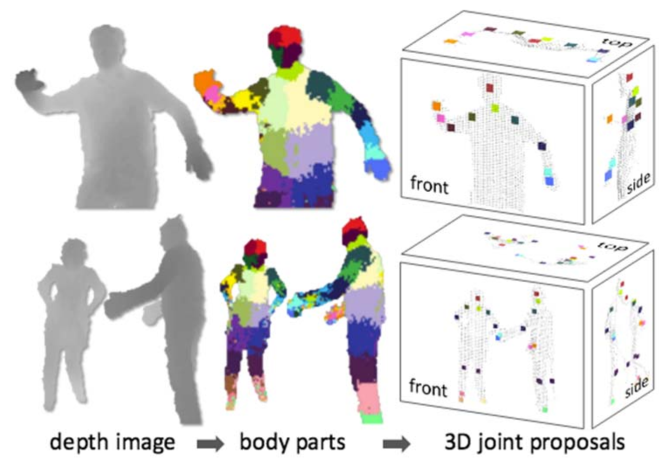
*Felzenszwalb, et al , 2010. Object detection with discriminatively trained part based models. [4]*

# Human Detection using depth data

- A “random forest” classifier labels each pixel according to body part
- Used in Microsoft’s Kinect
- About 1M training images

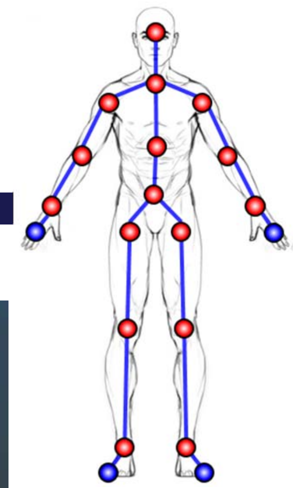


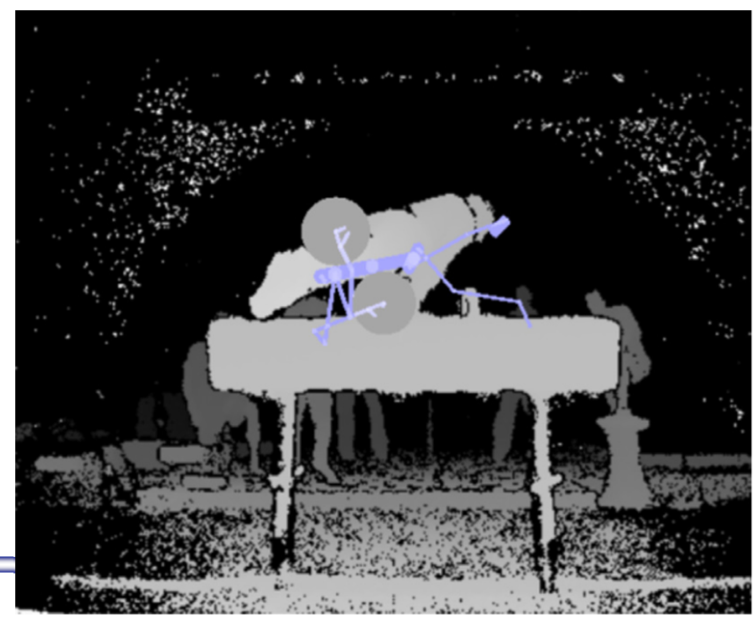

*Shotton, Jamie, et al. "Real-time human pose recognition in parts from single depth images“ [5]*

# Skeleton Estimation in Kinect

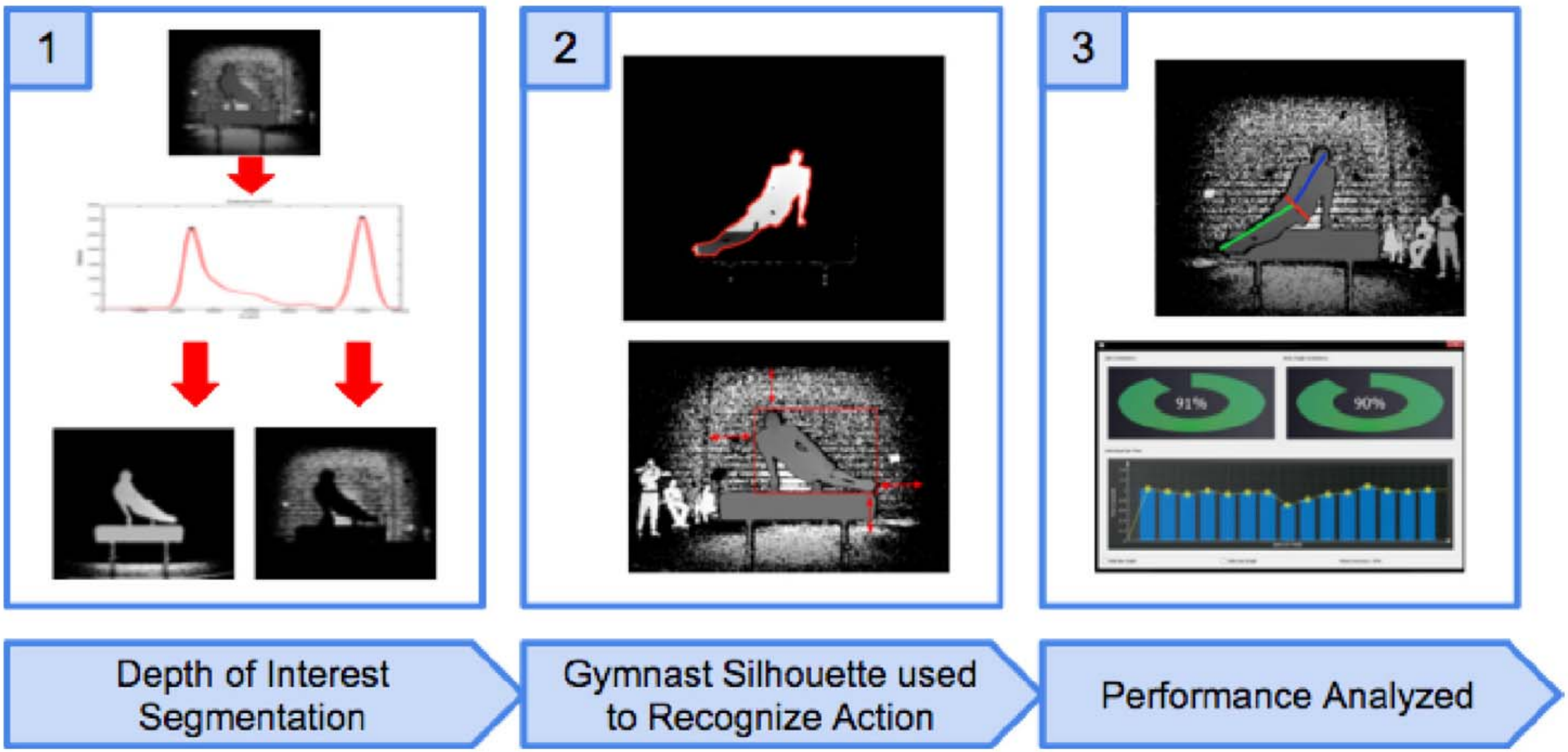


- Starting from a torso point, construct skeleton


- Problem – since it is trained on upright poses, it generates noisy and inaccurate data when applied to gymnasts



# Our Approach



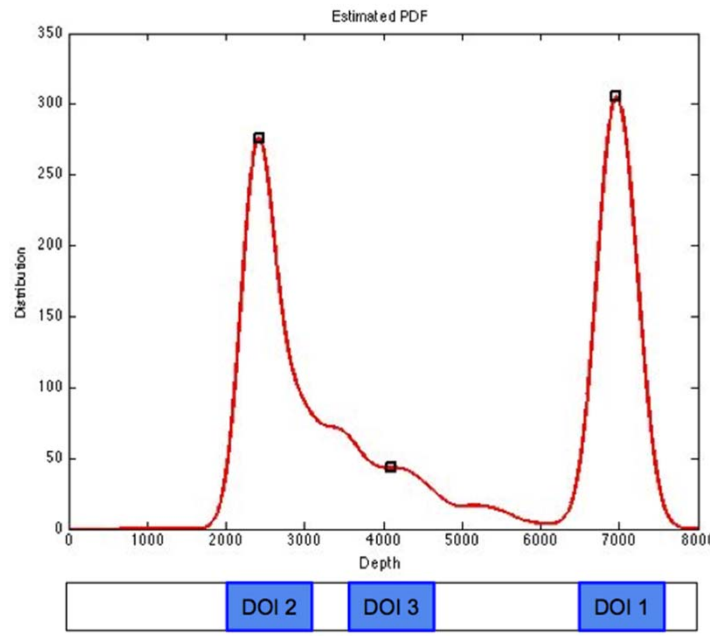
# Depth of Interest Segmentation

- Segment scene based on depth
- Steps
  - Select *n* pixels randomly
  - Describe each with a Gaussian function, and sum these

$$P(x) = \sum_{i=1}^{n} exp\left[\frac{-(x-D(x_i))^2}{2 \times MAXDEPTH}\right]$$

  - Identify peaks in this distribution

- Each peak is a proposal for a segmentation

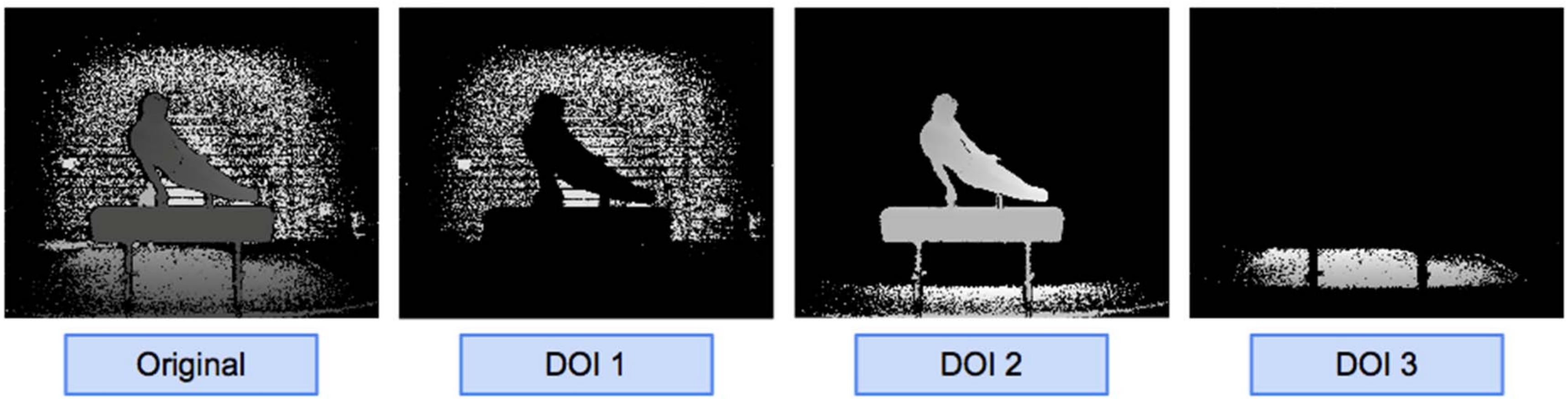



A window around each peak is used for segmentation

*Note: the stationary pommel horse is automatically removed from the scene*

# Depth of interest segmentation

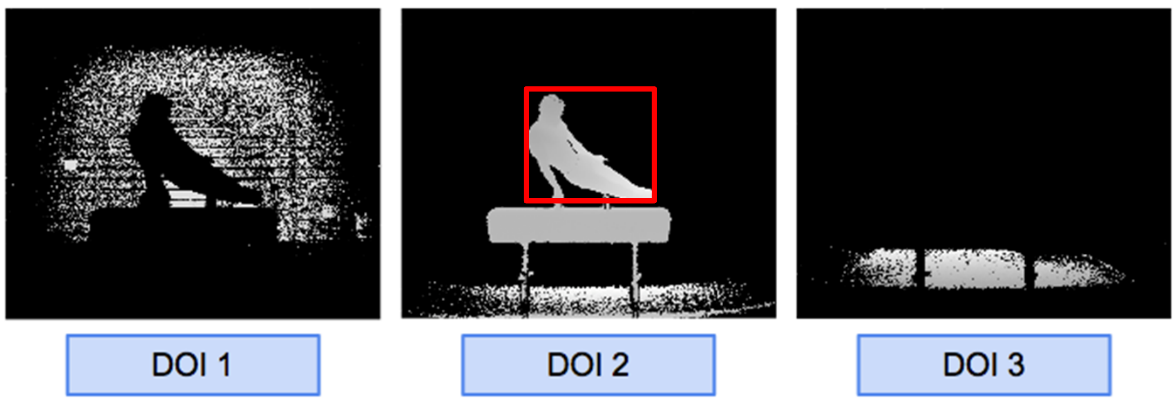
- Experimentally, the human is completely contained in the segmentation corresponding to one of the top three proposals 97.8% of the time




- Segmentation greatly reduces the amount of data that later stages of the pipeline need to process.
- On average, non-zero pixels are 37.8% of image size

# Human Detection from Silhouette

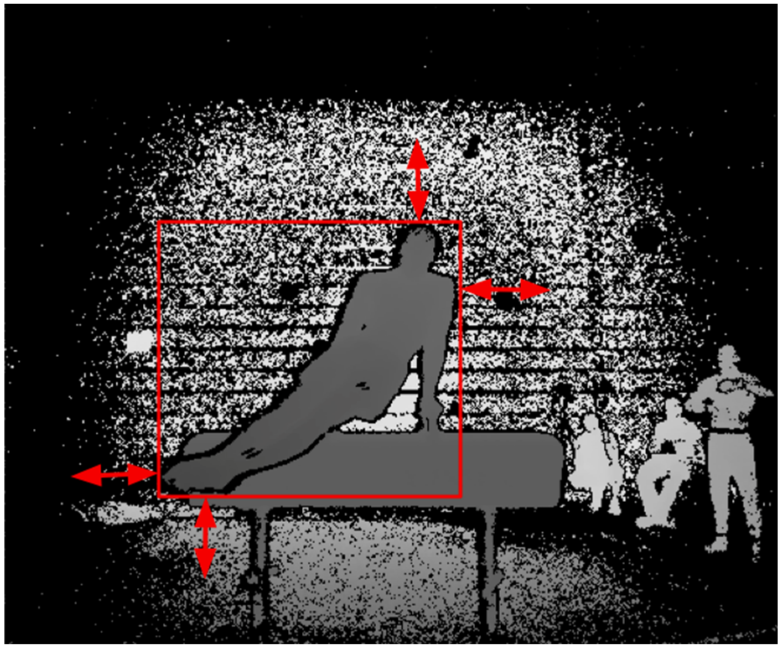
- Identified depths of interest are input to a HOG based detector trained to identify silhouettes
- HOG features are computed on depth imagery, treating this data as a grayscale image to obtain the gradients




- SVM sliding window classifier
  - Single class: human vs not human
  - Trained on a large variety of gymnast poses; robust to changes in body size and orientation

# Recognition of Spinning Activity

- Need to detect when the gymnast is spinning
- Compute a Silhouette Activity Descriptor:
  - Width, height of silhouette
  - Depth values at the left and right sides
  - Change in top, bottom, left, and right image coordinates compared to the previous frame

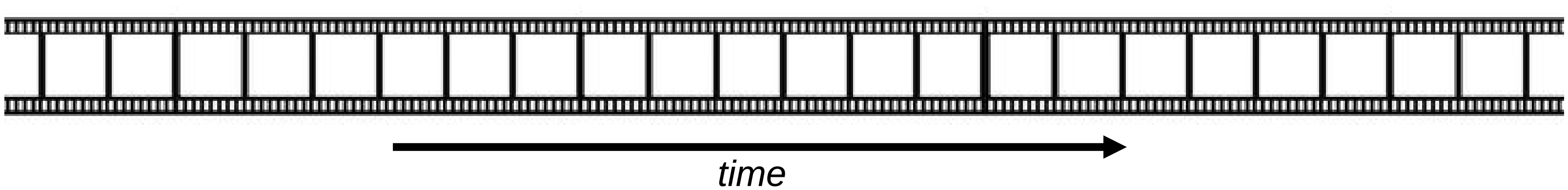


*The descriptor is computed for each frame*

# Recognition of Spinning Activity

- A support vector machine classifier was trained to recognize spin/no spin
  - Radial basis function kernel

$$K(x_i, x_j) = \exp -\gamma \, \|x_i - x_j\|^2$$

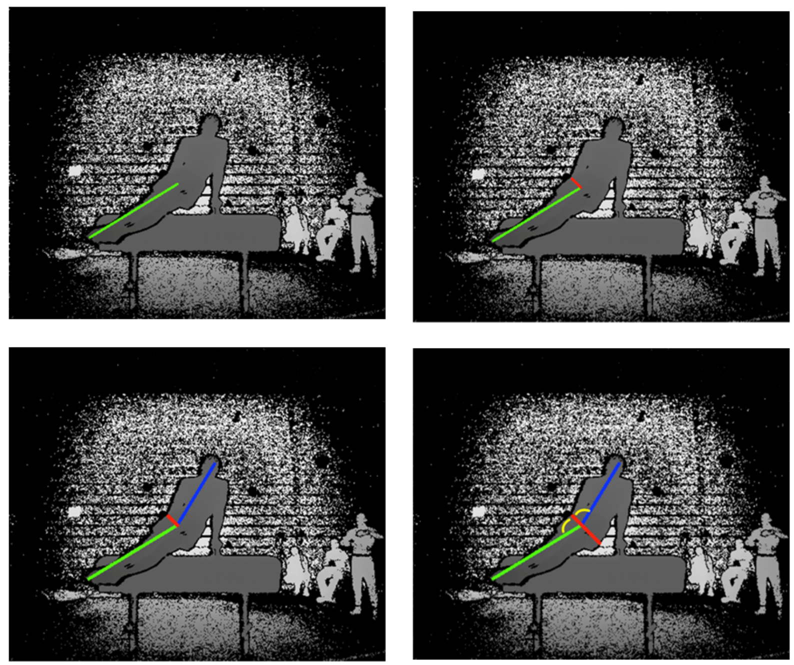



- Temporal smoothing
  - Classifier is applied to each frame
  - Classifications are smoothed over 5 frames

$$c_i = \left\lfloor \frac{1}{5} \sum_{j=-2}^{2} c_{i+j} \right\rceil$$

# Performance analysis of spins

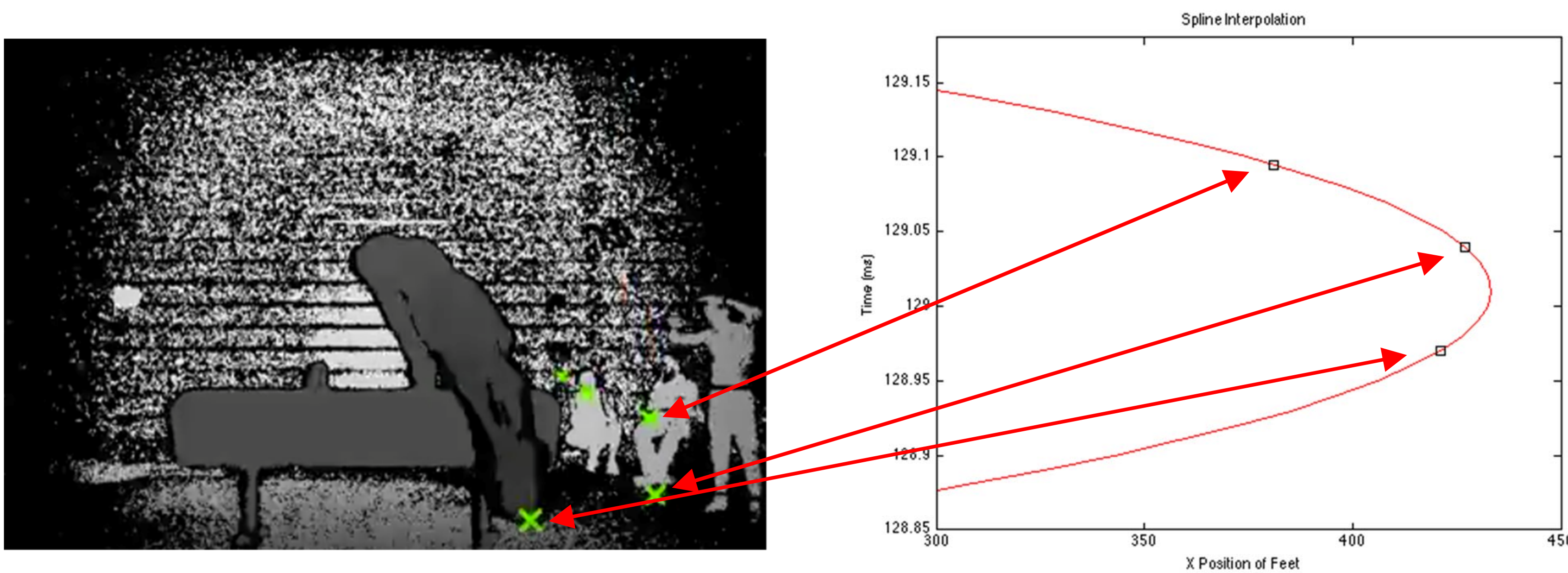
- Goals:
  - Track the position of the feet
  - Track body angle
- Procedure:
  - From the body centroid, identify the longest vector to the body contour
  - Then identify the shortest vector – this is the waist
  - Using the bend in the body, identify the second longest vector



*Feet are assumed to the lower of the two long vectors*

# Timing spins

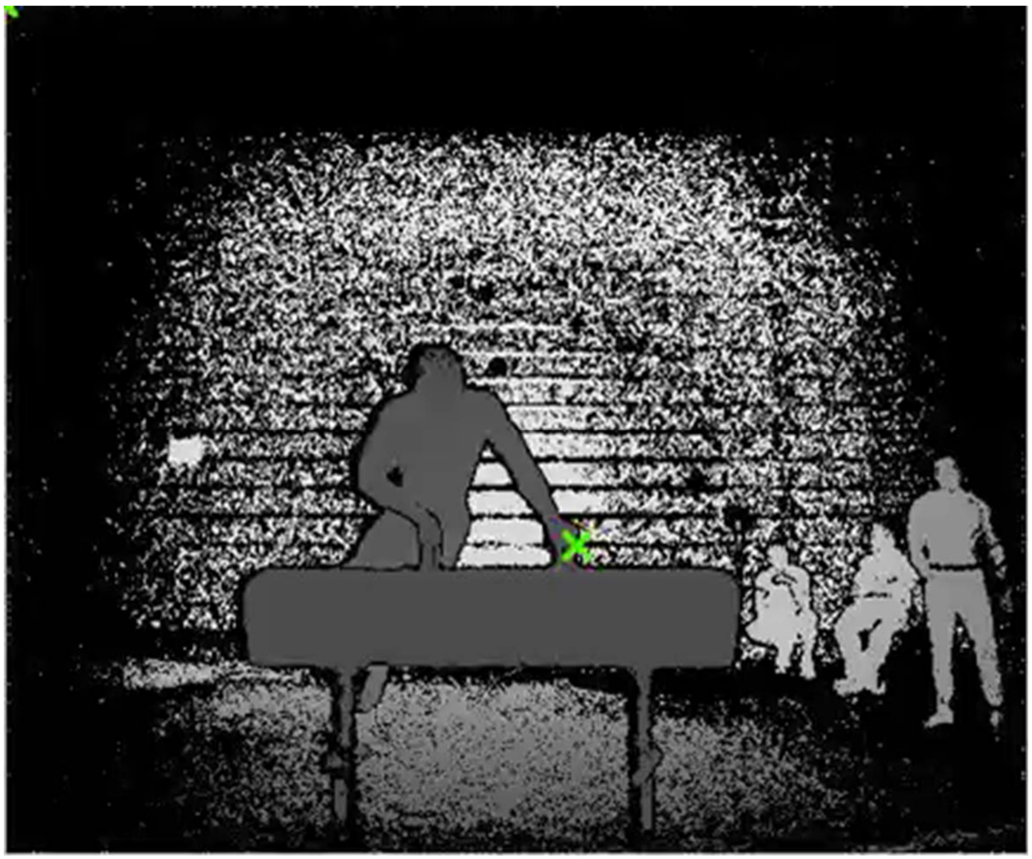
- Find the times when the feet achieve greatest deviation in x
- Fit to a cubic spline, to interpolate the exact time of an extrema
- The duration of the spin is the amount of time between consecutive left extrema or consecutive right extrema.



# Spin detection video

https://www.youtube.com/v/LRK8vK6NXfg

# Spin detection (slow)

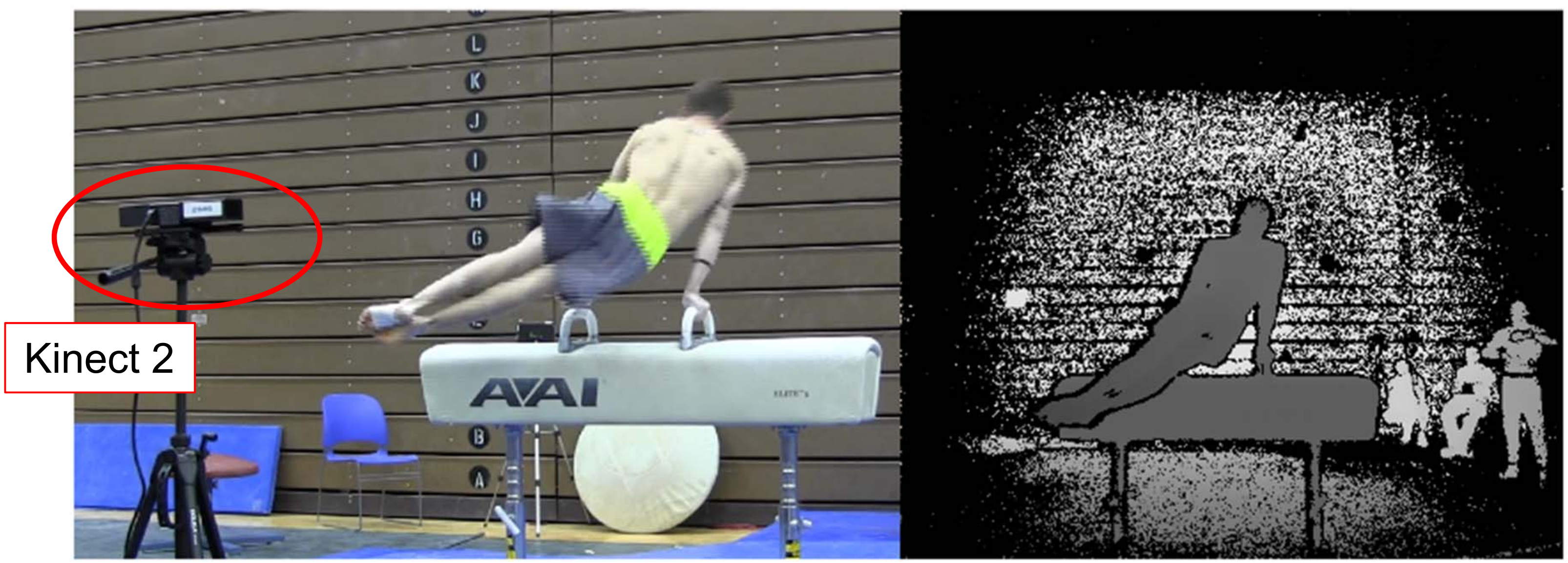


https://www.youtube.com/v/IFTE_Lna9So

# Data collection

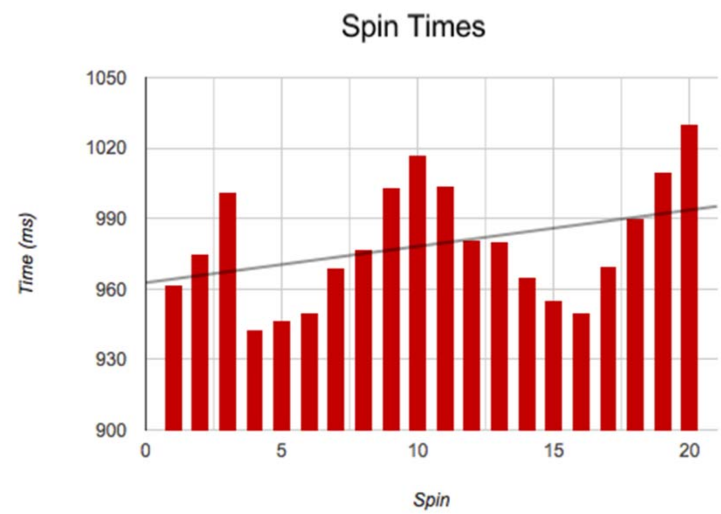
- 39 routines
- 10115 depth images
- Dataset available at http://hcr.mines.edu

- Annotated with
  - Spinning (yes/no)
  - Location of head and feet
  - Time of extrema



# Evaluation

- Activity recognition
  - Data split into 5024 training frames and 5091 testing frames
  - Classified spin/no spin with 94.83% accuracy

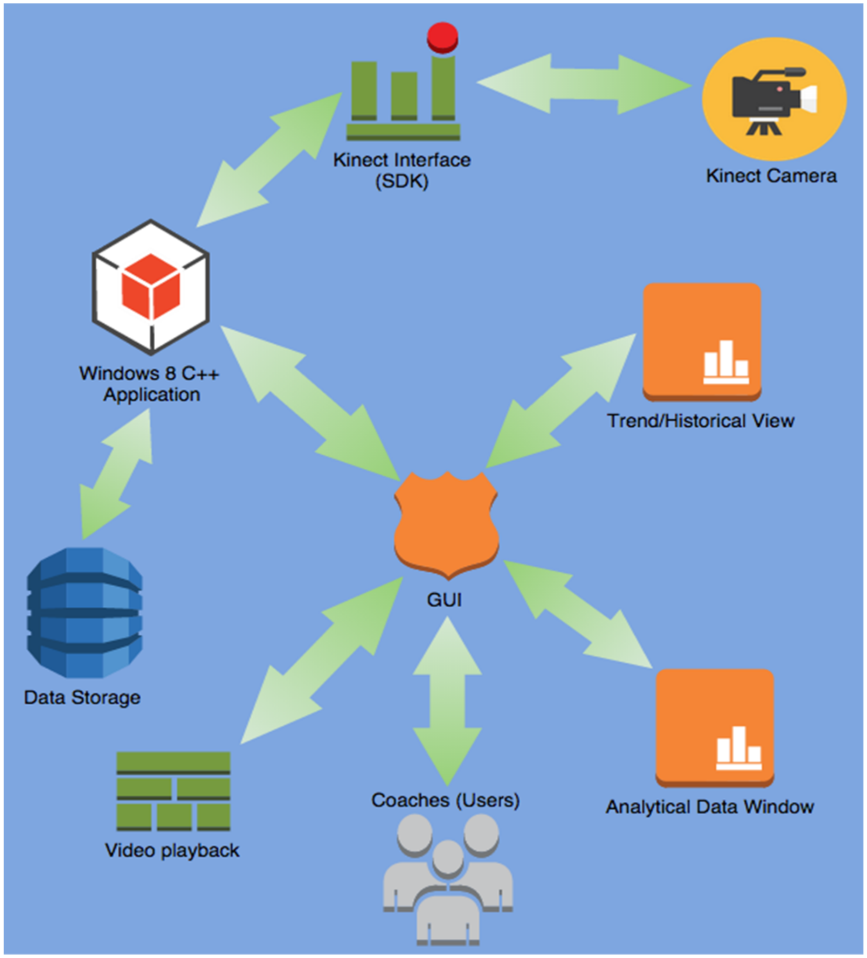



- Spin times
  - RMS error was 12.99 ms compared to ground truth

Average spin time for a top gymnast is 960ms, with a standard deviation of only 25ms

# Case study – application development

- An application was developed for use by coaches for training
- Software
  - C++, OpenCV, Qt



# User Interface

# User Interface

$$Consistency = \frac{Mean - Std\,Deviation}{Mean}$$

# Conclusions

- Introduced an automated system to provide an analysis of a gymnast's performance, using a portable 3D camera
- Steps:
  - Detect a gymnast using novel "depth of interest" method
  - Identify when a gymnast is performing circles
  - Analyze their performance
- Performance
  - Identify a depth of interest with 97.8% accuracy
  - Detect spinning with 93.8% accuracy
  - Analyze spin consistency with less than a 13ms RMSE
- Created an app for gymnastics coaches
- Dataset with ground truth

# Thank you!

## References

[1] Federolf, P., et al. "Impact of skier actions on the gliding times in alpine skiing." Scandinavian journal of medicine & science in sports, 2008

[2] Moore, Jason K., et al. "Rider motion identification during normal bicycling by means of principal component analysis." Multibody System Dynamics, 2011

[3] Sam Mikulak - Pommel Horse - 2012 Visa Championships - Sr. Men https://www.youtube.com/watch?v=19N6uruAyos

[4] Felzenszwalb, et al , 2010. Object detection with discriminatively trained part based models. IEEE PAMI

[5] Shotton, Jamie, et al. "Real-time human pose recognition in parts from single depth images" Communications of the ACM 56.1 (2013): 116-124.