

# Automatic Assessment of Surgical Ergonomics

Group 17 - Boyoung Zhao, Eric Han Presenter : Eric Han

#### **Project Overview**

- Using Intel RealSense D415 and Cubemos software development kit to find all essential joints positions
- Use joint positions to calculate angles between joints
- Return ROSA (Rapid Office Strain Assessment) and RULA (Rapid Upper Limb Assessment) scores



### **Paper Summary**

#### RGB-D ergonomic assessment system of adopted working postures

Ahmed Abobakr<sup>a,\*</sup>, Darius Nahavandi<sup>a</sup>, Mohammed Hossny<sup>a</sup>, Julie Iskander<sup>a</sup>, Mohammed Attia<sup>a</sup>, Saeid Nahavandi<sup>a</sup>, Marty Smets<sup>b</sup>

<sup>a</sup> Institute for Intelligent Systems Research and Innovation (IISRI), Deakin University, 75 Pigdons Rd, Waurn Ponds, Victoria, 3216, Australia <sup>b</sup> Ford Motor Company, 29500 Plymouth Rd, Livonia, MI, 48150, USA

- Vision based ergonomic posture assessment system using RGB-D cameras and deep-learning to find body joint angles and RULA score.
- Relies on computer generated synthetic data as well as motion capture sequences to generate training data

### Introduction and Background

- Musculoskeletal disorders account for 31% of all work-related injuries and illness cases (Bureau of Labor Statistic, 2016)
- Recent studies have used the Kinect camera along with its software development kit to analyze the adopted posture and evaluate the RULA score
  - Many limitations when using these methods
- Need a skeleton-free holistic posture analysis system



#### Dataset

- Collecting a labelled training dataset of postures for workers of different anthropometric measures is infeasible, labeling reference joints is expensive and error-prone
- Dataset is automatically generated from a computer that uses the MakeHuman software
- Models are animated using retargeting postural information from motion capture (mocap) sequences
- BlenSor was used to add artificial noise to the data using a realistic and statistically verified noise model

#### Workflow

- Reference joints angles for training were obtained using an inverse kinematics step
  - virtual model had virtual markers placed on their body
  - Each marker corresponds to a mocap marker
- Skeletal model is animated by minimizing the error between the corresponding marker positions in the skeletal model and in the captured data
- Minimization function is

$$\sum_{i \in m} w_i ||x_i^{exp} - x_i(q)||^2,$$

• Generated synthetic depth images and corresponding joint angles make up the dataset for training the deep ConvNet regression model

## Workflow (cont.)

- Input depth image of the posture
- Output joint angles vector required for computing the RULA score
- Network can approximate a function that maps input images of working postures to joint angles
- Result is a posture vector that can be used to compute the RULA score



#### Results

- Model was applied on a real dataset of 24K postures for 6 subjects of different body shapes
- Reference angles were computed using recorded mocap sequences in real conditions.

Table 8 Prediction errors on real data.

Joint name	MAE (deg.)	Scaled MAE (%)	RMSE (deg.)	Scaled RMSE (%)
Trunk rotation	3.23 ± 3.34	1.79 ± 1.86	4.64	2.58
Trunk twist	3.13 ± 3.05	$1.74 \pm 1.70$	4.37	2.43
Trunk bend	$2.30 \pm 2.09$	$1.16 \pm 1.28$	3.10	1.72
L. Elevation	$4.13 \pm 4.70$	$1.88 \pm 2.14$	6.26	2.84
R. Elevation	$4.04 \pm 4.34$	$1.83 \pm 1.98$	5.93	2.70
L. Shoulder	4.19 ± 4.32	$2.33 \pm 2.40$	6.02	3.34
R. Shoulder	4.27 ± 4.65	$2.40 \pm 2.59$	6.31	3.51
L. Elbow	$4.14 \pm 4.54$	3.18 ± 3.49	6.14	4.72
R. Elbow	$4.19 \pm 4.97$	3.22 ± 3.82	6.50	5.00
L. Wrist flexion	$2.59 \pm 2.46$	$1.85 \pm 1.76$	3.58	2.56
R. Wrist flexion	$2.76 \pm 2.72$	$1.97 \pm 1.94$	3.87	2.77
L. Wrist deviation	$1.06 \pm 1.06$	3.03 ± 3.04	1.50	4.29
R. Wrist deviation	$1.15 \pm 1.22$	3.29 ± 3.49	1.68	4.79
L. Wrist twist	3.05 ± 2.75	$1.70 \pm 1.53$	4.11	2.28
R. Wrist twist	3.58 ± 3.21	$1.99 \pm 1.79$	4.81	2.67
Average	$3.19 \pm 1.57$	$2.23 \pm 1.12$	$4.27 \pm 2.32$	$2.94 \pm 1.64$

#### Results (cont.)

 Achieved a joint angle MAE error of 3.19 ± 1.5° and RMSE error of 4.27 ± 2.32° and an average RULA grand score prediction agreement of 89% over both right and left body sides, with a substantial Kappa index level of 0.71

#### Table 9

The effect joint angle errors on RULA postural scores.

RULA Score	RMSE	Accuracy Po	kappa (k)
Upper arm Right	0.29	0.92	0.88
Upper arm Left	0.32	0.90	0.86
Lower arm Right	0.22	0.95	0.82
Lower arm Left	0.20	0.96	0.84
Wrist score Right	0.50	0.78	0.67
Wrist score Left	0.50	0.78	0.67
Score A (arm and wrist) Right	0.39	0.86	0.78
Score A (arm and wrist) Left	0.41	0.84	0.76
Score B (neck, trunk and legs)	0.64	0.82	0.63
RULA Grand Score Right	0.49	0.86	0.66
RULA Grand Score Left	0.51	0.85	0.67

#### Conclusion

- Proposed a semi-automatic ergonomic assessment model using RGB-D cameras and a deep-learning network
- Composed of a segmentation model that detects and segments the person in the scene and a neural network that is trained to estimate body joint angles from a single depth image
- The reference joint angles are obtained using a biomechanical model while the prediction model is trained using synthetic depth images
- Corresponding RULA score has a prediction accuracy of 89%, which is more accurate and reliable than pre-existing models

#### **Assessment - Pros and Cons**

- Pros
  - General paper was well organized
  - Images were very helpful to the user, especially someone who might not be as informed
  - Everything mentioned was explained in great detail
- Cons
  - Did not explain how the angles were calculated
  - Did not provide the results of previous models
  - Transitioning subjects without providing relation

#### Assessment - Future Work

- Improve upon 89% RULA agreement
- Improve upon 5 FPS (NVIDIA Titan X GPU)
  - Efficiency of model
- Return information on how to improve upon posture after outputting RULA score

#### **Assessment - Relevance**

- Our project also uses a RGB-D camera and deep learning software development kit to calculate RULA scores
  - Helps understanding of deep learning algorithm
- Use 3.19 ± 1.5° MAE for body joint angles and average RULA grand score prediction agreement of 89% as comparisons for our results

#### References

Ahmed Abobakr, Darius Nahavandi, Mohammed Hossny, Julie Iskander, Mohammed Attia, Saeid Nahavandi, Marty Smets, RGB-D ergonomic assessment system of adopted working postures, Applied Ergonomics, Volume 80, 2019, Pages 75-88, ISSN 0003-6870, https://doi.org/10.1016/j.apergo.2019.05.004.

#### Questions?

