

# **Stroke Patient Daily Observation System**

Jaired Collins<sup>1</sup>, Joseph Warren<sup>1</sup>, Mengxuan Ma<sup>3</sup>, Rachel Proffitt<sup>2</sup>, Marjorie Skubic<sup>3</sup>

<sup>1</sup> Computer Information Systems Department, Missouri Southern State University, Joplin, MO.

<sup>2</sup>Occupational Therapy Department, <sup>3</sup> Electrical Engineering and Computer Science Department, University of Missouri, Columbia, MO.

### Abstract

Stroke is a leading cause of long-term adult disability. Stroke patients can recover through rehabilitation programs prescribed by occupational therapists (OT); however, an individualized rehabilitation program can reduce recovery times compared to traditional ones. We propose a daily activity observation system (DAOS) that uses a Kinect v2 sensor to collect and retrieve motion data. The depth information allows us to perform action recognition, while skeleton data is used to do Range of Motion assessment. Action recognition accuracy is 97% on a multi-class kitchen action dataset. Combining an action and its opposite improves recognition rates. Assessment values are verified with a Vicon system.

## **Action Recognition**

- We use histogram of oriented 4D normals (HON4D) to compute a video descriptor [2].
  - Normals are computed as:

$$\mathbf{n} = \nabla S = \left(\frac{\partial z}{\partial x}, \frac{\partial z}{\partial y}, \frac{\partial z}{\partial t}, -1\right)^T$$

where  $\mathbf{n}$  is then normalized,  $\widehat{\mathbf{n}}$ 

• The bins of the histogram are set as the vertices of a polychoron,  $\mathcal{P} = \{\mathbf{p}\}$ . Bin contributions are calculated as  $c(\widehat{\mathbf{n}}_j, \mathbf{p}_i) = \max(0, \widehat{\mathbf{n}}^T \mathbf{p}_i)$ 

### **Assessment Results**

Left and Right Hand Trajectories in X-Z Plane in Meters



### Introduction

- 795,000 suffer from a stroke in the U.S. [1]
  The Kinect is a cheap, accurate camera sensor
  - Color camera
  - Depth information
  - Skeleton data
- Daily Activity Observation System (DAOS)
  - Action Recognition
  - Assessment
- No current system integrates action recognition and assessment!



After computation of HON4D descriptors, they are normalized.



Major assessment :

Distance:

 $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}$  **O Speed:** 

5							
J.5							
-0.3	-0.2	-0.1	0 >	< <sup>0.1</sup>	0.2	0.3	0.4

#### Fig. 3. 2D Hand symmetry for PrepOpen



#### Fig. 4. 2D Chest sway for PrepOpen

Assessment speed accuracy was verified against a Vicon system with average and standard deviation:

Fig. 1. Researcher in the DAOS

### Dataset

We collected an in-house dataset consisting of common kitchen tasks, as in Table 1 and Fig. 2.
 9 people x 28 actions x 2 = 504 total.

WashSink	WashRinse	PickUpTop	PutDownTop		
Wash	PronCut	Pickl InBottom	PutDown		
Dishwasher	Γιεροάι	Γισκοροσιοπ	Bottom		
PronStir	PrenOnen	OpenTop	CloseTop		
riepotii	перорен	Cabinet	Cabinet		
DronClose	Manipulate	OpenBottom	CloseBottom		
riepolose	Stove	Cabinet	Cabinet		
Manipulate	Manipulate	WalkIntoNot	MalkIntoHold		
Microwave	SinkOn	Hold	vvaikimuonoiu		
Manipulate	Manipulate	WalkOutNot			
Fridge	SinkOff	Hold	VValkOuthold		
PickUp	PutDown	WalkAround	WalkAround		
Counter	Counter	NotHold	Hold		
Table 1. Chosen kitchen tasks for our dataset.					

 Graphs of hand symmetry and chest sway
 To account for occlusion, when any of the upper body joints that are used to perform assessment are inferred or missing, all skeleton data for that instance is set to zero.

# **Recognition Results**

- The in-house dataset in Table 1 was subdivided into smaller datasets as in Table 2.
  SVM with a quadratic kernel to classify the data
- Accuracies are highest on datasets whose actions are different categories. The scores are lower for when an action and its opposite are included, such as opening a jar and closing it.

Dataset Name	Actions	Accuracy		
PickPutDataset1	PickUpCounter PutDownCounter PickUpTop PutDownTop PickUpBottom PutDownBottom	37.5%		
PickPutDataset2	PickUpCounter & PutDown PickUpTop & Putdown PickUpBottom & PutDown	69.4%		
OpenCloseDataset1	OpenTopCabinet CloseTopCabinet OpenBottomCabinet CloseBottomCabinet	54.2%		
OpenCloseDataset2	OpenTopCabinet & Close OpenBottomCabinet & Close	75.0%		
MixedDataset1	ManipulateFridge CloseBottomCabinet WalkIntoKitchenHold	97.2%		
MixedDataset2	WashSink WalkAroundKitchenNotHold PrepStir	97.2%		
Table 2. SVM results of datasets.				

 $\mu = 0.06$   $\sigma = 7.85$  (inches/second)

	Max Arm Extension, Left	Max Arm Extension, Right	Mean Speed of Hand, Left	Mean Speed of Hand, Right
WashRinse	30.2	25.6	18.3	10.5
PrepOpen	22.4	22.2	8.1	11.6
WIKHold	24.1	21.9	17.3	19.2
MSinkOn	24.9	24.5	12.1	21.1
PUCounter	27.4	22.6	20.3	12.1

Table 3. Max arm extensions and mean speeds.

### Conclusions

- We present a novel solution for occupational therapists to create more personalized care for stroke rehabilitation patients.
- Recognizes several actions with a high degree



Fig. 2. Unprocessed (left) and processed (right) depth images in data collection kitchen.

of certainty using HON4D as a global descriptor
 Assessment on critical metrics such as arm extension, mean velocity, and max velocity
 Allows a therapist to easily see problem areas or improvements over time to better provide care for a stroke victim

### References

 "Rehabilitation therapy after a stroke," Nov 2015. Available: http://www.stroke.org/
 O. Oreifej and Z. Liu, "Hon4d: Histogram of oriented 4d normals for activity recognition from depth sequences," in 2013 IEEE Conference on Computer Vision and Pattern Recognition, June 2013, pp. 716–723.

This material is based upon work supported by the National Science Foundation under Award Number: CNS-1659134.