Kinder-Gator: The UF Kinect Database of Child and Adult Motion

<u>Aishat Aloba</u>¹, Gianne Flores¹, Julia Woodward¹, Alex Shaw¹, Amanda Castonguay²⁺, Isabella Cuba³⁺, Yuzhu Dong¹, Eakta Jain¹, Lisa Anthony¹

¹Dept of CISE, University of Florida, Gainesville, FL USA ²University of Southern Maine, ME USA ³Vassar College, Poughkeepsie, NY USA

⁺ Work conducted while these authors were summer interns at the University of Florida.







Disney Pixar characters (Image courtesy of www.wallpapercave.com)

Existing Datasets

• Datasets of Adult motions

- MOBO (Gross and Shi, Tech Rep'01)
- MADS (Kolykhalova et al., INTETAIN'16)
- G3D (Bloom et al., CVPR '12)
- K3Da (Leightley et al., APSIPA '15)
- OTHER DATASETS (van Boxtel)
- Datasets of Child-like motions
 - MPI Database (Volkova et al., PLoS ONE'14)



C. Adult expressing pride (Volkova et al. '14)





Addressing the Limitations of Existing Datasets

• Movements and Poses of Children differ from those of adults (Animation Addicts '13)









The Human Motion Database: A Cognitive and Parametric Sampling of Human Motion [9] Guerra-Filho and Biswas (2012)

• 50 children and adults (ages 7 to 82) and 70 actions (e.g., walk, wave)





Example gestures: Jump, Kick, and Step Up



Addressing the Limitations of Existing Datasets







Kinder-Gator

A Kinect database of 10 Children and 10 adults performing 58 Motions Naturally https://jainlab.cise.ufl.edu/pose-perception.html





Motions in Kinder-Gator



This paper explores the use of a guessability study to examine child-defined gestures with Kinect. Applying a Wizard-of-Oz approach, gestures were elicited from six children (age 3-8) through a series of 22 task stimuli including object manipulation, navigation-based tasks, and spatial interaction. Gestures were video recorded, transcribed, and coded by three researchers employing an inductive, qualitative method of analysis. Five

[9]. Participants were asked to provide gestures for 22 referents while being shown a series of prompts and directives. Gestures and body movements were video recorded, categorized, and coded for the purpose of comparing and contrasting gestures by age gender, and degree of user familiarity with Kinee This paper provides a preliminary examination of the challenge

involved in applying the guessability methodology as a means

enges in the development of an MMOE, including pose selection, training, recognition, an presentation methods. © 2011 International Federation for Information Processing Published by Elsevier B.V. All rights reserved.

taneously facilitate fast learning and accurate recall of ges-tures [7]. In the human-computer interaction (HCt) field, a variety of 2D gesture recognition algorithms have been dea distance. First, users can use one-handed and two-handed gestures to directly issue commands. Second, users can use veloped for touchscreens and tablets. These either use a statistical model (e.g. [8]), or various forms of template match-ing (e.g. [1, 3, 10]). Outside the HCI field, gesture recogand two-handed gestures with an accuracy of 92.7%-96.2%.

their non-dominant hand to modulate single-hand gestures

Our evaluation shows that the system recognizes one-hander



ABSTRACT

Categories and H.5.1 [Information

ABSTRACT A sedentary lifestyle is linked to many health problems, including diabetes, heart disease, and

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Game design

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A recontancy interspect to indiar to indiary means proteiness including undiacces, teals undexec, and Active games attempt to offer a solution by encouraging players to be more physically active t the use of entertaining media. We present a framework for a massively multiplayer online gs (MMOE), that combines elements of persuasive technology and massively multiplayer online gs provide players with a customized, social gaming experience with the potential for long-term ment and measurable physical benefits. We then examine our own exergaming system, sensor network for active play (SNAP), to assess its suitability in an MMOE context. We then address several technical and

Gestures are natural components in human-human interaction and human neuromuscular control is well-evolved to simul two ways of gesturing commands in thin air to displays a

Motions in Kinder-Gator

Warm-Up (9 motions)	Exercise (14)	Mime (16)	Communication (19)
Raise your hand	Put your hands on your hip and lean to the side	Push an imaginary button in front of you	Point at the camera
Wave your hand	Walk in place	Fly like a bird	Motion someone to come here
Bow	Run in place as fast as you can	Kick a ball	Draw a [circle, square, Triangle] in the air
Bend your Knee	Jump as high as you can	Kick a ball as hard as you can	Draw the letter [A,C,K,M,X] in the air
Bend your other Knee	Do Five Jumping Jacks	Climb an imaginary ladder	Make the letter [Y,M,C,A,K,P,T,X] with your body





Warm-up Motions (9)

• Used in day-to-day activities









Exercise Motions (14)

• Induce physical exertion and used in exercise and fitness activities









Mime Motions (16)

• Conceptualize imaginary objects









Communication Motions (19)

Used to convey information









Demographics

Gender





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10 Children: M= 6.70 years, SD: 1.42 **10 Adults:** M = 23.40 years, SD = 4.33



The Kinect v1.0

Tracks 3D positions of 20 joints along 3 dimensions





Coordinate Frame centered at Kinect



Joints tracked by the Kinect



Study Setup

- Participants stood within an area (47 x 47 inches) forward-facing the Kinect
- Duration of motion is dependent on the motion being performed



Child performing the T-pose





Study Setup

- Participants stood within an area (47 x 47 inches) forward-facing the Kinect
- Duration of motion is dependent on the motion being performed







Data Collection

• A total of 19 RGB videos and 1159 motion trials (58 motions * 20 participants)

Timestamp	HipCenterX	HipCenterY	HipCenterZ	•••	User-ID	Motion
48546673.98	-0.0419986	-0.1512957	3.057717		103	Raise-your-hand
48546708.98	-0.04312875	-0.151742	3.058163		103	Raise-your-hand
48546740.99	-0.04372106	-0.1516228	3.058321		103	Raise-your-hand
48546772.99	-0.0443305	-0.1512319	3.059047		103	Raise-your-hand

Dataset Example





Applications

Recognition

Animation



Generate "child-like" avatar Make the letter "Y" with your body Lift your leg to one side motion

Human Motion Characteristics





Animation: Cross-Generational Morphing

• The dynamic scaling law was used to transform adult motion to child motion (Dong et al. [MIG' 17])



Adult











Animation: Cross-generational Morphing

• 'Child-like' motion created using a style translation algorithm is more similar to the motion of a child (Dong et al. [Eurographics' 18])





Child in the middle is the result of converting adult to child

Eurographics Poster Session (Today 12:00-13:15)



Recognition

Gait Recognition



Human Activity Recognition



Jumping Jacks



Jump

Stroke Gesture Recognition







Human Motion Characteristics

• Perceive the differences between child and adult motions (Jain et al. [TAP' 16])



Adult





Rendering every 10th frame of the jumping jacks motions for one child and one adult.



Human Motion Characteristics (Ongoing Work)

- Extract spatial and temporal gait features to quantify the differences between child and adult motions (Ongoing work)
- Walk in place, Walk fast, Run, Run fast

Spatial Features	Temporal Features			
Step Height	Step Time			
Step Width	Cycle Time			
Relative Step Height	Cycle Frequency			
Walk Ratio	Cadence			
	Step Speed			



Cadence



Conclusion

- Kinder-Gator is a Kinect database containing 58 motions performed by 10 children (ages 5 to 9) and 10 adults (ages 19 to 32)
- The database contains 19 RGB videos and 1159 motion trials
- The database is publicly available at:

https://jainlab.cise.ufl.edu/pose-perception.html

 Application of the database includes animation, recognition, and human motion characteristics of children and adults







Aishat Aloba



Gianne Flores

Thank You!

Contact Authors

init.cise.ufl.edu jainlab.cise.ufl.edu



Julia Woodward

Alex Shaw







Lisa Anthony





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