Real-World Machines

A computer, a television camera, and a mechanical arm have now been combined into a system with enough artificial intelligence to recognize blocks of various sizes and shapes and to assemble them into structures without step-by-step instructions from an operator. The system can perceive the blocks visually, determining their size and their location on a table. It can stack them into a tower while accomplishing another goal, for example, of making the tower as high as possible with the given blocks. Or, it can be told to sort the blocks by size into neat, separate stacks.

Development of this kind of system, which was demonstrated at M.I.T. this spring, is an early stage of research on principles that will give machines engaged in routine tasks greater flexibility through their ability to see their work. Even simple vision would allow a machine to grasp one object without relying on its being absolutely positioned, or to pick up an object it had dropped, or to recognize defects.

Long range goals of work directed by Marvin L. Minsky, Professor of Electrical Engineering, and Seymour A. Papert, Visiting Professor of Applied Mathematics, envisage machines with finer and more varied visual abilities and more manual dexterity than are required for such semi-routine tasks. Work is progressing on binocular vision, color vision, the ability to perceive textures, touch sensors, improved mechanical hands and other areas whose development is necessary for accomplishing significant real-world tasks. Outlining goals such as these, especially the ability to program machines to acquire and use a substantial fund of knowledge about the real world, reveals the extent of scientific and engineering progress toward "artificial intelligence."

For vision, the system demonstrated at M.I.T. this spring uses "image dissector" cameras, controlled by a computer, which can make use of the television images in various ways: as input to the learning process, or for testing a computer's visual perception.

Segmenting images using localized histograms and region merging

Authors

J. Ross Beveridge, Joey Griffith, Ralf R. Kohler, Allen R. Hanson, Edward M. Riseman
And from Bruce Draper

The schema system

Bruce A. Draper, Robert T. Collins, John Brollo, Allen R. Hanson & Edward M. Riseman

International Journal of Computer Vision 2, 209–250(1989) | Cite this article

288 Accesses | 135 Citations | 3 Altmetric | Metrics
CSU History (Very Partial)

• Image Understanding
• 3D Model Based Object Recognition
• Satellite Reconnaissance
• Object Recognition in General
• Face Recognition
• Video Understanding
• Gesture Recognition
• Communicating with Computers
A visualization of RNIs in Skeleton based Action Recognition (SkeletonVis)
The visualization of RNIs provided by the Skeleton based Action Recognition Toolkit provides insights into models embedded in Recurrent Neural Networks in the domain of skeleton-based Action Recognition. Using two primary methods for visualizing the properties learnt by a trained LSTM Network, namely, Sensitivity analysis and Activation Maximization, we present case studies on datasets commonly used for Action Recognition. Additionally, users can upload their own models and visualize their trained models.
Last updated August 30, 2019.

Robust Staged RANSAC Tracking
The Robust Staged RANSAC Tracking algorithm is useful for stabilizing video from a handheld camera. It is particularly well suited to the handheld video in the Point and Shoot Face Recognition Challenge where there is distinct camera motion following a person and yet for much of the video much of the scene background remains fixed as though the camera had been locked down on a tripod.
Last updated February 28, 2014.

PaSC Software Support Package
CSU distributes a package of software for working with the Point and Shoot Face Recognition Challenge. This software comes in two forms, a completely self-contained virtual machine and source code. Both distributions include meta-data useful for working with PaSC. They also include everything needed to run the CSU provided baseline algorithms and to generate ROC curves.
Last updated June 11, 2013.

Optimized Correlation Output Filters Toolkit (OCOFTools)
The Optimized Correlation Output Filters Toolkit (OCOFTools) is a software package offered for those interested in experimenting with David Botelho's Optimized Correlation Output Filters. This work is summarized in David Botelho's Dissertation as well as CVPR papers from 2009 and 2010. Be aware that Colorado State University has a patent covering the filter construction technique; the code is available for non-commercial research and education purposes only. License details are available through the download page.
Last updated October 10, 2012.

The 2011/2012 Face Recognition Baselines
This release was prepared to support the Good, Bad and Ugly (GBU) Challenge problems. More information about the GBU Challenge may be found in An Introduction to the Good, the Bad and the Ugly Face Recognition Challenge Problem and at the MIST Site. In terms of what is most current, the PaSC is a more recent and better challenge problem for most purposes. However, GBU remains a challenging face recognition problem with ample opportunity for the community to benchmark improvement.
Last updated August 7, 2012.

FaceL
Facel is a simple turnkey demonstration of live face recognition core code. It is constructed to work with video feeds from laptop cameras and webcams. It is designed to be easily trained for up to about 10 people and serve as a demonstration of technology largely for educational purposes. Unfortunately, the turnkey version from Mac OS is not compatible with more recent releases of OS X. With appropriate knowledge of Mac OS or Windows FaceL can still be installed from the source distribution and run successfully. However, as it is based on older versions of Python and OpenCV it should not be viewed as trivial to install.
Last updated September 21, 2009.

Evaluation of Face Recognition Algorithms
This system was our first major effort at releasing a turnkey series of face recognition algorithms along with evaluation support software. As of now, 2014, it is eleven years old and still being downloaded by some. As an educational tool we believe it can still be of value. The associated information concerning evaluation of algorithms using the original FERET protocol may be of use to anyone wishing to replicate much earlier experiments on arguably the first major face recognition challenge problem. The algorithms themselves in this package are dated and should not be taken as meaningful benchmarks of modern algorithms performance.
Last significant update May 2003.
Some Samples of Past Work

Face Recognition in real-time at CSU around 2006
Text and Face Images (~2006)

A two-time Academy Award-winner, this handsome, amiable leading man with a stoic, deadpan style made his now-infamous major film debut in director Lawrence Kasdan's "The Big Chill" (1983). Though his scenes ended up being excised nearly completely, the cutting room disaster only delayed Costner's rise to superstardom. In recompense, Kasdan gave him the prominent, flashy role of the wild...

12/12/19

CSU CS410 Fall 2019, © Ross Beveridge
Faces & Illumination Part 1

Faces & Illumination Part 2

$k$ distinct images

Image Set 1

$\theta = (\theta_1, \theta_2, \ldots, \theta_k)$

Grassmann Manifold $G(k, n)$

$k$ distinct images

Image Set 2

$X \rightarrow Y$
Faces & Illumination Part 3

Diagram showing similar faces and their similarity scores.
More Interactive Play
FaceL

Click a face in the video to enroll.
Labels: 0  Faces: 0

Enrollment Count: 64

Train Labeler  Clear Labels
How to Start a Trend


David S. Bolme
Colorado State University

Based on:
Visual Object Tracking using Adaptive Correlation Filters.
Computer Vision and Pattern Recognition, June 2010.

MOSSE Track: Visual Vehicle Tracking Using a Thermal Video Sensor
11,441 views • Apr 12, 2010

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<tbody>
<tr>
<td>Visual object tracking using adaptive correlation filters</td>
<td>1622</td>
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<td>DS Bolme, JR Beveridge, BA Draper, YM Lui</td>
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<td>2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition</td>
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<td>Recognizing faces with PCA and ICA</td>
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<td>Computer vision and image understanding 91 (1-2), 115-137</td>
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</table>
DARPA Mind's Eye
Fort Indiantown Gap
Highlight Reel

Copyright 2012 iRobot Corp.
... and then came CNNs

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky  
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Ilya Sutskever  
University of Toronto  
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Geoffrey E. Hinton  
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Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called “dropout” that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.
Communicating with Computers

User-Aware Shared Perception for Embodied Agents

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James Pustejovsky
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Brandeis University
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Jaime Ruiz
Isaac Wang
Department of Computer Science & Engineering
University of Florida
Gainesville, FL 32611
Email: jaime.ruiz@ufl.edu
Hello

Diana is an embodied agent who can hear, speak and see.
Our Goal

• Better communication when …
  • A person and computer are focused upon a physical task
  • Tasks are AI classics: e.g. Blocks World, Set a Table

• Why is this interesting

• Our Tasks stand in for most everyday tasks where …
  – There is shared perception of a common setting
  – Verbal communication is grounded by context
  – There is shared awareness of body/embodiment
  – Communication is grounded by seeing each other
How We Started

- Elicitation studies between two people solving blocks world tasks.

Layout of Blocks

Microsoft Kinects

2-Way Communication

Signaler

Builder

Supported by DARPA & ARL through contract #W911NF-10-2-0066
What We Learned ... Examples

RA:
move, front;

RH:
into point, down

RA:
move, up;

RH:
into thumbs, up

Body:
move, back;
What We Learned ... Gestures

24,503 labeled instances
8:08:02 of video
~550 hours of labeling effort
5,060 unique physical movements

110 Gestures occur 20 or more times and from multiple people.
Our current system uses primitive 32 hand poses
Combined with arm and body motion, there are 31 distinct non-verbal communicative actions.
Speech, Gesture, or Both

Gestures alone are roughly as effective as words alone in blocks world: a physical and cooperative task.

Gestures and words used together are more effective than either used alone.
What We Can Do

Blocks World Domain
Recap What you Just Saw

- Diana sees and hears
  - She understands the user’s speech and is conversant
  - She understands the user’s non-verbal communication
  - She integrates verbal and non-verbal communication
  - Communication is grounded in shared perception and a task

- In just the first few seconds
  - “Hello Nikhil, I am ready to go”
    - Diana saw Nikhil approach, she waves in greeting
    - Diana focuses her attention, her gaze, on Nikhil
    - Thumbs up gesture while saying “ready to go”

- ...

- And one minute forty seconds later
  - Diana and Nikhil have together built a staircase
How Does Diana Do We Do It?

Live Gesturing and Speech

Kinect®

Segmented Depth Data

Speech Recognition

DCNN Gesture Recognition

Semantic “Packages”

VoxSim
Just the Gesture Side

- CNNs trained on Kinect depth images recognize 31 distinct hand poses
- LSTMs trained on Kinect skeleton data recognize 8 distinct arm motions
- Training is derived from our 8 hours of labeled data
  - The EGGNOG (Elicited Giant Gallery of Naturally Occurring Gestures) dataset is publicly available
- Typically neural networks require multiple GPUs
  - But a very high-end laptop with GPUs now supports the full system
- Gesture label data as it is recognized gets passed along to the cognitive agent, i.e. Diana
The Cognitive Agent, aka Diana

No I am not expecting you to read these slides!
Key Idea: Grounded Language

Risking gross oversimplification, two approaches

Traditional
Final ‘truth’ lies in predicates.

Blocks world actually used to illustrate value of logic based representation, and ONLY predicates

Example 1: Blocks World

We introduce the predicate \textit{on}(X,Y) read as “X is directly on top of Y” to represent the above configuration of blocks as:

\begin{verbatim}
    on(a,b). /* on.1 */
    on(b,c). /* on.2 */
    on(c). /* on.3 */
\end{verbatim}

Brandeis
Final ‘truth’ ties directly into physical simulation

Concepts grounded in physical modeling, e.g.
The Unity Engine
VoxML

The Embodied Avatar Conceit

There is now a growing conceit about AI agents. Interact with your agent as you would with a person. We have taken a step down this road in terms of an agent that can see, speak, listen, share perception, and interact with a person to solve tasks.
## We Still Do Vision!

<table>
<thead>
<tr>
<th>TITLE</th>
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<th>YEAR</th>
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<tbody>
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<td>Inception and ResNet features are (almost) equivalent</td>
<td></td>
<td>2020</td>
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<tr>
<td>D McNeely-White, JR Beveridge, BA Draper</td>
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<td>Cognitive Systems Research 59, 312-318</td>
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<td>D Patil, BA Draper, JR Beveridge</td>
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<td>P Narayana, JR Beveridge, BA Draper</td>
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<td>2019 International Joint Conference on Neural Networks (IJCNN), 1-8</td>
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<td>Analyzing multi-channel networks for gesture recognition</td>
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<td>MN Teli, BA Draper, JR Beveridge</td>
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<td>Adapting RGB Pose Estimation to New Domains</td>
<td></td>
<td>2019</td>
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<td>G Mulay, BA Draper, JR Beveridge</td>
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<td>2019 IEEE 9th Annual Computing and Communication Workshop and Conference ...</td>
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<td>Rotary manifold for automating a paper-based Salmonella immunoassay</td>
<td>1</td>
<td>2019</td>
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<td>CS Carrell, RM Wydallis, M Bontha, KE Boehle, JR Beveridge, BJ Geiss,</td>
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<td></td>
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<td>RSC Advances 9 (50), 29078-29086</td>
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</tbody>
</table>
And from CS 510 Last Spring

The images were collected on the Barry M. Goldwater Air Force Range (BMGR) in Arizona. Provided as a courtesy to CS 510 to demonstrate proof of concept.

Label: Mule Deer
white tailed deer 0.75579
mule deer 0.23304494
bobcat 0.005833398

Label: White Tail Deer
bobcat 0.5680608
white tailed deer 0.3562632
gray fox 0.046345647

Label: Mule Deer
Top 3:
Classification white tailed deer 0.499
mule deer 0.4859644
coyote 0.0058485395

Label: White Tale Deer
Top 3:
Classification mule deer 0.62270
white tailed deer 0.3751
coyote 0.0005578
Recognition Accuracy Example

Confusion matrix, transfer learning with inception-resnet-v2, acc = 0.97238

From students Brandon Gildemaster and Yan Wang
So What About Jobs

Quick informal survey of LinkedIn on December 10 2019

<table>
<thead>
<tr>
<th>Field</th>
<th>Salary</th>
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<tr>
<td>Software Engineer</td>
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<td>Computer Vision</td>
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<td>Machine Learning</td>
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<tr>
<td>Cybersecurity</td>
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<tr>
<td>Bioinformatics</td>
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<td>Computer Graphics</td>
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<tr>
<td>Natural Language Processing</td>
<td>1,000</td>
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<tr>
<td>High Performance Computing</td>
<td>989</td>
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CS410 – A Good Word: Much CS 410 is designed to train skills that feed directly into Computer Vision. We even published a paper on this design.