



มหาวิทยาลัยมหิดล  
น้อมรัตนบารมี

# Overview Biometrics and Medical Imaging

Asst. Prof. Worapan Kusakunniran

Faculty of Information and Communication  
Technology, Mahidol University, Thailand



# Home Institute

- Faculty of Information and Communication Technology,  
Mahidol University, Thailand
- 6 Years Teaching
  - Bachelor of Science in ICT (International Program)
    - MM, Programming, AI, Image Processing
  - Master Program in Computer Science (International Program)
    - Methodology
  - Master Program in Game Technology and Gamification  
(International Program)
    - AI, CV
  - Ph.D. in Computer Science (International Program)
  - Ph.D. in Data Science for Health Care (Faculty of Medicine  
Ramathibodi Hospital and Faculty of Graduate Studies, Mahidol  
University)
    - Advanced Machine Learning



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# Education

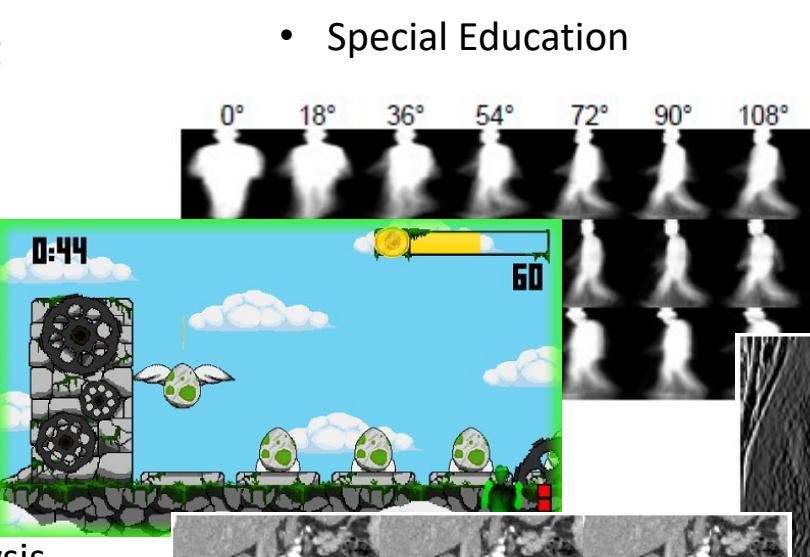


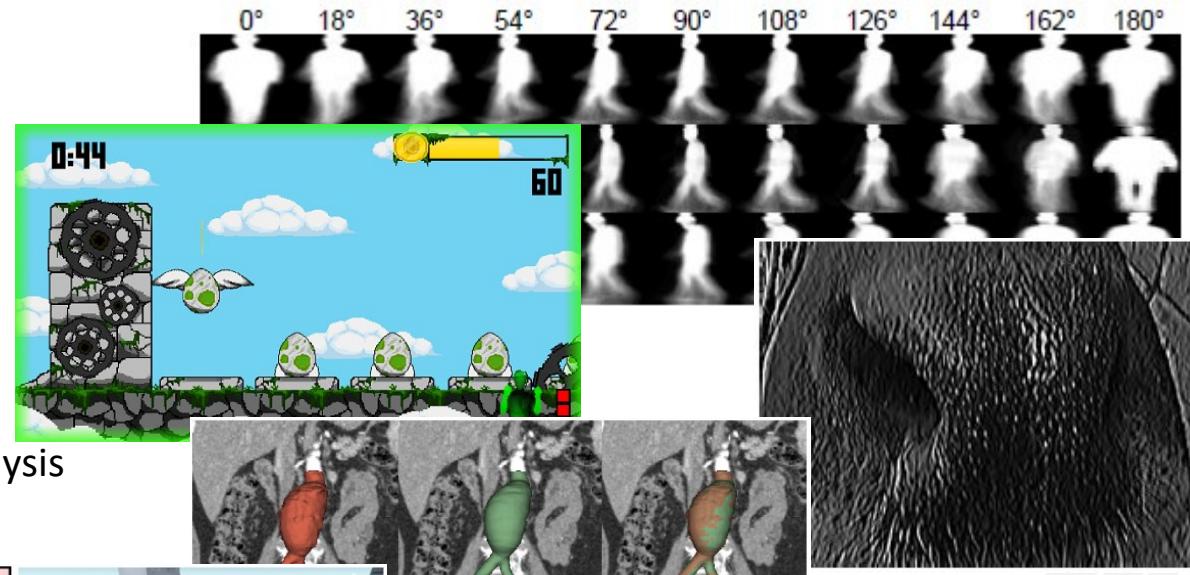
**UNSW**  
SYDNEY

- B.Eng. (**1<sup>st</sup> class honor with the University Medal**)
  - The School of Computer Science and Engineering
  - University of New South Wales
  - Australia
  - July 2008
- Ph.D.
  - The School of Computer Science and Engineering
  - University of New South Wales
  - NICTA
  - Australia
  - May 2013



# Research Areas of Interest

- Biometrics
  - Medical Image Processing
  - Image and Video Processing
  - Gait Recognition
  - Pattern Recognition
  - Computer Vision
  - Machine Learning
  - Data Analysis
  - Artificial Intelligence
  - Action and Behavioral Analysis
  - Object Tracking
  - Object Classification
  - Health Information System/Standard
  - Special Education





# Sample Projects

- Automatic Detection of Diabetes Retinopathy based on Digital Retinal Images, funded by Thailand Research Fund (TRF)
- Security Guard Re-identification by using Face Image, funded by Waller Security Service Co., Ltd.
- Activity and Behavior Recognitions: Automatic Interpretation of Human Motion Concepts in Images and Videos, funded by Mahidol University
- Development of Swamp Buffalo (*Bubalus Bubalis*) Identification using Biometric Feature, funded by Agricultural Research Development Agency (Public Organization)



## Sample Academic Services

- Fingerprint Interchange System Design Project, Central Institute of Forensic Science, 2018, **Ministry of Justice**
- Technical Advisory on Information and Communication Technology 2018, Central Institute of Forensic Science, **Ministry of Justice**
- Technical Advisory on Information and Communication Technology 2019, Central Institute of Forensic Science, **Ministry of Justice**
- Committee of Demonstration and Benchmark Test, Department of Consular Affairs, 2018, **Ministry of Foreign Affairs**
- Committee of Demonstration and Benchmark Test, Department of Consular Affairs, 2019, **Ministry of Foreign Affairs**



# Collaborations

- In house
  - Faculty of Physical Therapy
  - Faculty of Veterinary Science
  - Faculty of Nursing
  - Faculty of Medicine, Siriraj Hospital
  - Faculty of Medicine, Ramathibodi Hospital
- Overseas (recent)
  - Macquarie University
  - University of Technology Sydney (UTS)
  - National Institute of Advanced Industrial Science and Technology (AIST)
  - Tokyo University of Agriculture and Technology (TUAT)
  - Liverpool John Moores University (LJMU)
  - National Cheng Kung University (NCKU)
  - University of Bremen

## Co-authors

- |  |  |   |
|--|--|---|
|  | Jian Zhang<br>University of Technology, Sydney...                            | > |
|  | Qiang Wu<br>Associate Professor, School of C...                              | > |
|  | Hongdong Li<br>Australian National University                                | > |
|  | Kittikhun Thongkanchorn<br>Faculty of ICT, Mahidol University                | > |
|  | Yi Ma (马毅)<br>Professor of EECS, University of...                            | > |
|  | Liang Wang<br>National Lab of Pattern Recogniti...                           | > |
|  | Shin'ichi Satoh<br>National Institute of Informatics                         | > |
|  | Jos Vanrenterghem<br>Associate professor, KU Leuven ...                      | > |
|  | Dr Mark A Robinson<br>Liverpool John Moores University                       | > |
|  | Harco Leslie Hendric Spits<br>Warnars<br>Head of IS concentration at Doct... | > |
|  | Peter Haddawy<br>Mahidol University  | > |
|  | Anuwat Wiratsudakul<br>Department of Clinical Sciences ...                   | > |



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Google Scholar



Worapan Kusakunniran

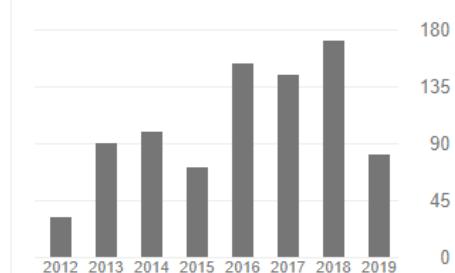
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Verified email at mahidol.edu - [Homepage](#)

Gait Recognition Biometrics Medical Image Processing Image and Video Processing  
Action and Behavioral Anal...

<input type="checkbox"/>	TITLE	CITED BY	YEAR
<input type="checkbox"/>	Multiple views gait recognition using view transformation model based on optimized gait energy image W Kusakunniran, Q Wu, H Li, J Zhang 2009 IEEE 12th International Conference on Computer Vision Workshops, ICCV ...	145	2009
<input type="checkbox"/>	Gait recognition under various viewing angles based on correlated motion regression W Kusakunniran, Q Wu, J Zhang, H Li IEEE transactions on circuits and systems for video technology 22 (6), 966-980	122	2012

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## Scopus Preview

Kusakunniran, Worapan

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Mahidol University, Nakhon Pathom, Thailand

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<http://orcid.org/0000-0002-2896-611X>

Subject area: [Computer Science](#) [Engineering](#) [Medicine](#) [Mathematics](#) [Social Sciences](#) [Energy](#) [Decision Sciences](#) [Health Professions](#)

Document and citation trends:



Documents by author

52

Total citations

685 by 381 documents



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# Professional Duties



**Asst. Prof. Dr. Worapan Kusakunniran**

ผศ. ดร. วรพันธ์ คุ้สกุลนิรันดร์

**Machine Vision and Information Transfer**

**(MVIT)**

[MVIT Facebook Page](#)

[MVIT Home Page](#)

## Contact Information

E-mail: [worapan.kun@mahidol.ac.th](mailto:worapan.kun@mahidol.ac.th) / [worapan\\_k@hotmail.com](mailto:worapan_k@hotmail.com)

Address (Salaya Campus): Faculty of Information and Communication Technology, Mahidol University, 999 Phutthamonthon 4 Road, Salaya, Nakhon Pathom 73170, Thailand  
Tel. (66) 02 441 0909, Fax. (66) 02 441 0808

Address (Phayathai Campus): Mahidol University Computing Center, Faculty of Information and Communication Technology, Mahidol University, Rama 6 Road, Rajathevi, Bangkok 10400, Thailand  
Tel. (66) 02 354 4333, Fax. (66) 02 354 7333



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# Topics

- Biometrics
  - Human Biometric
  - Animal Biometric
- Medical Imaging
  - Retinal Image
  - Aorta CT image
- Gaming Vision



# Human Biometric

- DNA, Face, Iris, Fingerprint, Palmprint, Gait
- Usages
  - Verification (1:1)
    - Input:
      - Biometric
      - Suspected ID
    - Output:
      - Yes or No or Undecided
  - Identification (1:N)
    - Input:
      - Biometric
    - Output:
      - ID or Undecided
  - Deduplicate (N:N)
    - Self
    - Master reference



# Human Biometric

- Applications
  - Civilian services
    - e-KYC
    - Voter registration
    - Tax collection enrollment
    - Citizens registration
    - Foreign employment
    - Passport tracking
    - Border control
    - Driver Licenses
  - Criminal justice/ Forensic science
    - Solving criminal cases

- Incomplete biometric image
- Need human experts
  - Identify minutiae
  - Confirm the identification output
- Return top-K rank





# Human Biometric

- Applications
  - Fingerprint
    - Types: Roll vs. Flat
    - Paper vs. Live-scan
    - Collection:
      - 10 prints (individuals OR 4-4-2)
      - 2 prints
      - Latent
    - Matching: 1:1 vs. 2:2 vs. 10:10



# Human Biometric

- Applications

- Standard

- ANSI/INCITS 381-2004 Finger Image-Based Data Interchange Format
    - ANSI/INCITS 377-2004 Finger Pattern Based Interchange Format
    - ANSI/INCITS 378-2004 Finger Minutiae Format for Data Interchange
    - ISO/IEC 19794-2 Finger Minutiae Format for Data Interchange
    - ISO/IEC 19794-3 Finger Pattern Spectral Data Based Interchange Format
    - ISO/IEC 19794-4 Finger Image Based Interchange Format
    - ISO/IEC 19794-8 Finger Pattern Skeleton Data Based Interchange Format
    - ANSI/NIST-ITL 1-2011: (Update 2013 and 2015) Data Format for the Interchange of Fingerprint, Facial, & Scar Mark & Tattoo (SMT) Information



# Human Biometric

- Applications

- NIST benchmarking

- MINEX: Minutiae Interoperability Exchange
    - PFT: Proprietary Fingerprint Template Evaluations
    - FpVTE: Fingerprint Vendor Technology Evaluation
    - NIST Evaluation of Latent Fingerprint Technologies

- Top-rank solutions

- NEC
    - Morpho (Idemia)
    - Cogent
    - Neurotechnology
    - ID3
    - Hisign
    - Innovatrics
    - AA Technology
    - Dermalog

The following entries summarize the verification performance documented in FpVTE 2003 and FRVT 2002. The most accurate face systems:

- 71.5% true accept rate @ 0.01% false accept rate
- 90.3% true accept rate @ 1.0% false accept rate.

The most accurate fingerprint system tested (NEC MST) using operational quality single fingerprints:

- 99.4% true accept rate @ 0.01% false accept rate
- 99.9% true accept rate @ 1.0% false accept rate

When multiple face images are available, the performance of face recognition can be improved [Grother3]. With four previous images in the gallery the error rates are substantially reduced

- 89.6% true accept rate @ 0.01% false accept rate
- 97.5% true accept rate @ 1.0% false accept rate

In FpVTE 2003, when four fingerprints were used for matching, the most accurate fingerprint system tested (NEC LST) always had true accept rates in excess of 99.9% at a FAR of 0.01%.



# Human Biometric

- Applications
  - Surveillance monitoring
    - No physical contact
    - Far distance
    - Alternative solution: GAIT
  - Other uses: disease diagnosis, abnormal walking, fall prevention





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# Human Biometric



Pattern Recognition Letters  
journal homepage: [www.elsevier.com](http://www.elsevier.com)

## Robust Gait Recognition using Hybrid Descriptors based on Skeleton Gait Energy Image

Lingxiang Yao<sup>a,c</sup>, Worapan Kusakunniran<sup>b</sup>, Qiang Wu<sup>c</sup>, Jian Zhang<sup>c</sup>, Zhenmin Tang<sup>a,\*\*</sup>, Wankou Yang<sup>d</sup>

<sup>a</sup>*School of Computer Science and Engineering, Nanjing University of Science and Technology, Nanjing, China*

<sup>b</sup>*Faculty of Information and Communication Technology, Mahidol University, Nakhon Pathom, Thailand*

<sup>c</sup>*School of Electrical and Data Engineering, University of Technology Sydney, Sydney, Australia*

<sup>d</sup>*School of Automation, Southeast University, China*

### ABSTRACT

Gait features have been widely applied in human identification. The commonly-used representations for gait recognition can be roughly classified into two categories: model-free features and model-based features. However, due to the view variances and clothes changes, model-free features are sensitive to the appearance changes. For model-based features, there is great difficulty in extracting the underlying models from gait sequences. Based on the confidence maps and the part affinity fields produced by a two-branch multi-stage CNN network, a new model-based representation, Skeleton Gait Energy Image (SGEI), has been proposed in this paper. Another contribution is that a hybrid representation has been produced, which uses SGEI to remedy the deficiency of model-free features, Gait Energy Image (GEI) for instance. The experimental performances indicate that our proposed methods are more robust to the cloth changes, and contribute to increasing the robustness of gait recognition in the unconstrained environments with view variances and clothes changes.

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# Human Biometric

- Techniques

- Faces

- Localisation using Haar-Cascade, DNN, HoG+SVM
    - Features:
      - Textures
      - Key points e.g. ASM, PSA
    - CNN

- Fingerprints

- Minutiae matching
    - Two fingerprints match if their minutiae points match
      - 25 to 80 minutiae (for good quality prints)

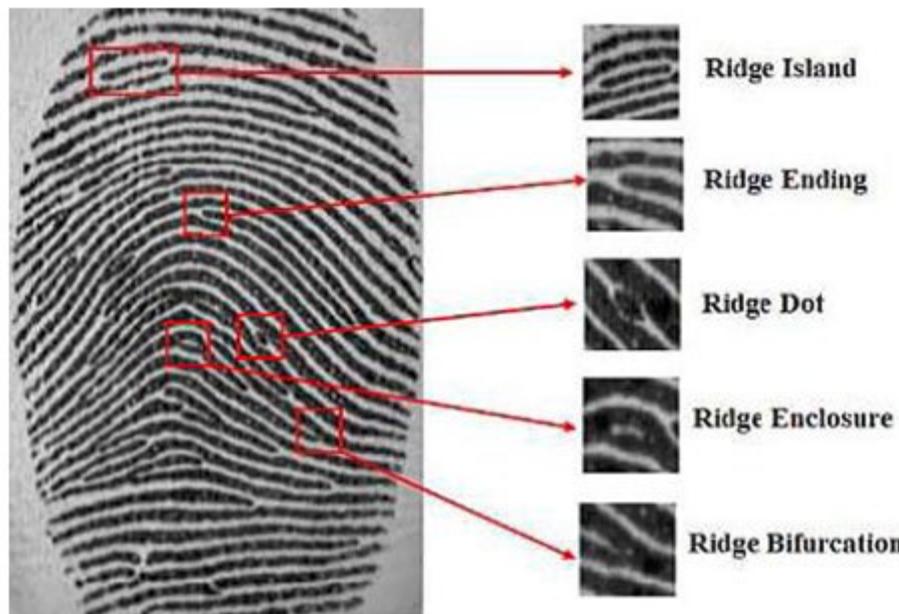


# Human Biometric

- Techniques

- Minutiae points

- Points where the ridge lines end or fork; OR
    - Local ridge discontinuities





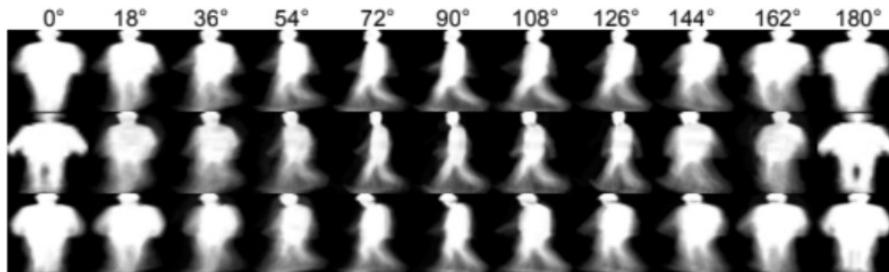
# Human Biometric

- Techniques
  - Gait
    - Model-based approach
    - Motion-based approach
    - Appearance-based approach
    - 3D gaits
    - CNN

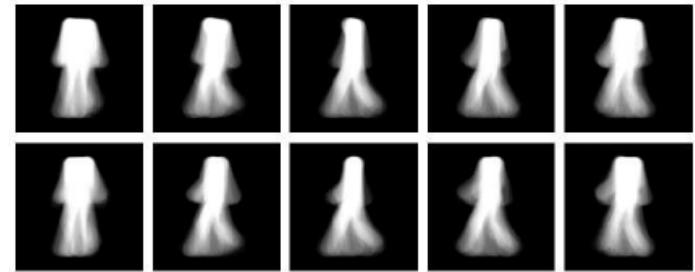


# Human Biometric

- Techniques
  - Gait
    - Apperance-based approach
    - Need silhouette segmentation



Kusakunniran, W., Wu, Q., Zhang, J., Li, H., & Wang, L. (2014). Recognizing gaits across views through correlated motion co-clustering. *IEEE Transactions on Image Processing*, 23(2), 696-709.

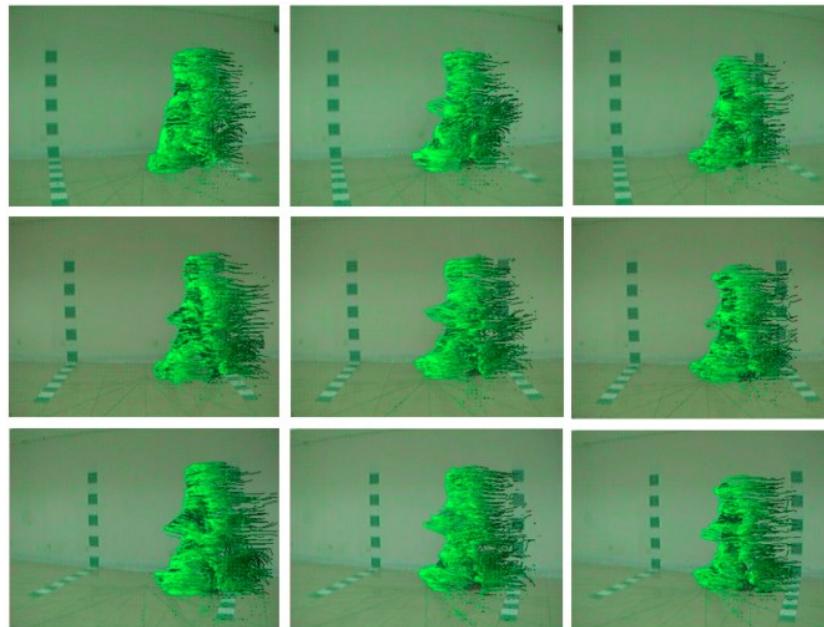


L. Yao, W. Kusakunniran, Q. Wu, J. Zhang, Z. (2018). Robust CNN-based Gait Verification and Identification using Skeleton Gait Energy Image, DICTA2018



# Human Biometric

- Techniques
  - Gait
    - Motion-based approach
    - No need of silhouette segmentation

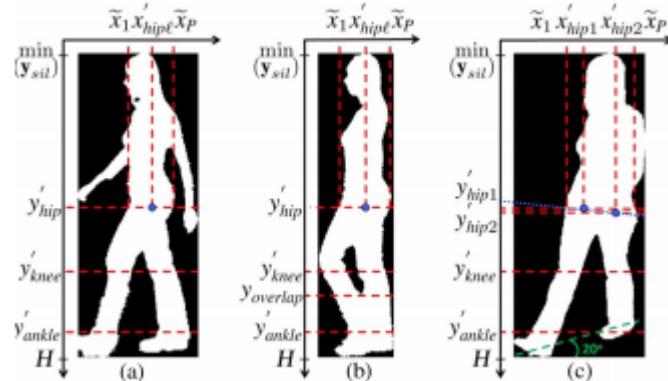


T. Satrupai, W. Kusakunniran, A Deep Trajectory based Gait Recognition for Human Re-identification, 1729 - 1732, Korea, October 2018, IEEE Region 10 Conference (TENCON)

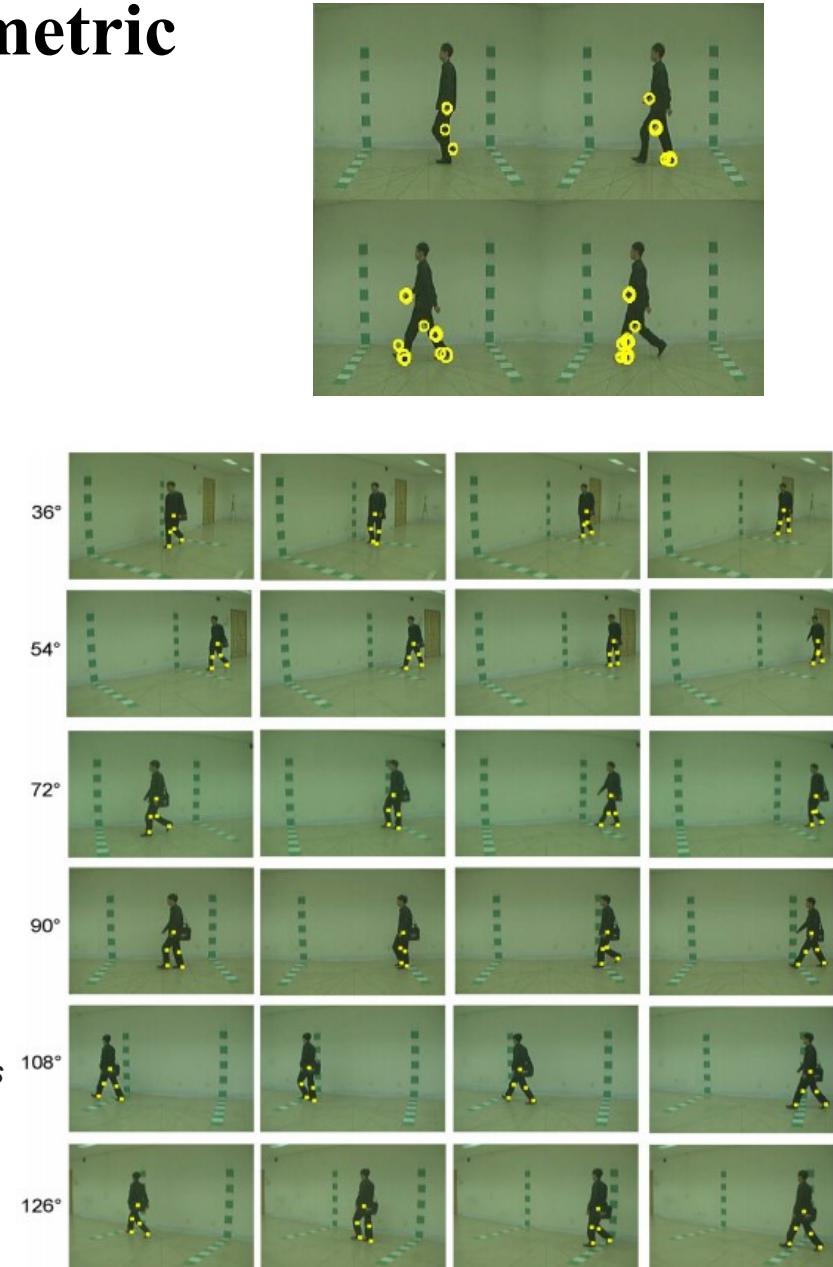


# Human Biometric

- Techniques
  - Gait
    - Model-based approach



Goffredo, M., Bouchrika, I., Carter, J. N., & Nixon, M. S. (2010). Self-calibrating view-invariant gait biometrics. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 40(4), 997-1008.





# Human Biometric

- Techniques
  - Gaits
    - Challenges
      - View (i.e. walking direction, camera angle)
      - Speed
      - Cloth
      - Shoe
      - Floor



# Human Biometric

- Techniques

- Gaits

- Performances

- Normal walking (covering 0 – 180 degrees)

- ❖ One camera
      - ❖ Two cameras
      - ❖ Three cameras
      - ❖ Four cameras

- View changes

- ❖ Cross-views
      - ❖ Multi-views

System	0°	18°	36°	54°	72°	90°	108°	126°	144°	162°	180°	Average
3 cameras	100	91	76	91	99	96	82	97	98	97	97	93
4 cameras	100	99	99	100	95	97	99	98	96	100	98	98
5 cameras	100	100	100	98	99	99	99	99	99	97	99	99

Kusakunniran, W., Wu, Q., Zhang, J., & Li, H. (2012). Cross-view and multi-view gait recognitions based on view transformation model using multi-layer perceptron. *Pattern Recognition Letters*, 33(7), 882-889.



# A Comprehensive Study on Cross-View Gait Based Human Identification with Deep CNNs

Zifeng Wu, Yongzhen Huang, *Member, IEEE*, Liang Wang, *Senior Member, IEEE*,  
Xiaogang Wang, *Member, IEEE*, and Tieniu Tan, *Fellow, IEEE*

**Abstract**—This paper studies cross-view gait based human identification with deep convolutional neural networks (CNNs). With a priori knowledge of probe view, we propose to find the most discriminative changes in probe view by comparing the feature maps of different probe views. We then propose a novel framework based on deep CNNs to identify human subjects in various scenarios, namely, cross-view gait based human identification.

TABLE 2  
Comparison with Kusakunniran et al.'s Method [12]  
and Yu et al.'s Baseline [6] under Normal Walking  
Conditions on CASIA-B by Accuracies (%)

Deep convolutional neural networks have been shown to be effective for gait recognition. To the best of our knowledge, this is the first comprehensive evaluation in terms of various scenarios and network architectures. The

Probe view	Gallery view	Ours	CMCC [12]	NN [6]
0°	18°	95.0	85	23.8
54°	36°	98.5	97	29.8
54°	72°	98.5	95	21.8
90°	72°	99.5	96	81.5
90°	108°	99.5	95	87.9
126°	108°	99.0	98	37.1
126°	144°	97.0	98	43.1
0°	36°	73.5	47	4.4
54°	18°	91.5	65	8.9
54°	90°	93.0	63	17.7
126°	90°	92.0	78	15.3
126°	162°	83.0	75	2.4
54°	0°	47.5	24	4.0
54°	108°	89.5	53	16.9
90°	36°	67.5	41	6.9
90°	144°	66.0	41	1.6
126°	72°	90.5	60	21.0
126°	180°	43.0	22	3.6



# Human Biometric

## GaitSet: Regarding Gait as a Set for Cross-View Gait Recognition \*

Hanqing Chao<sup>1†</sup>, Yiwei He<sup>1†</sup>, Junping Zhang<sup>1‡</sup>, JianFeng Feng<sup>2</sup>

<sup>1</sup>Shanghai Key Laboratory of Intelligent Information Processing, School of Computer Science

<sup>2</sup>Institute of Science and Technology for Brain-inspired Intelligence

Fudan University, Shanghai 200433, China

{hqchao16, heyw15, jpzhang, jffeng}@fudan.edu.cn

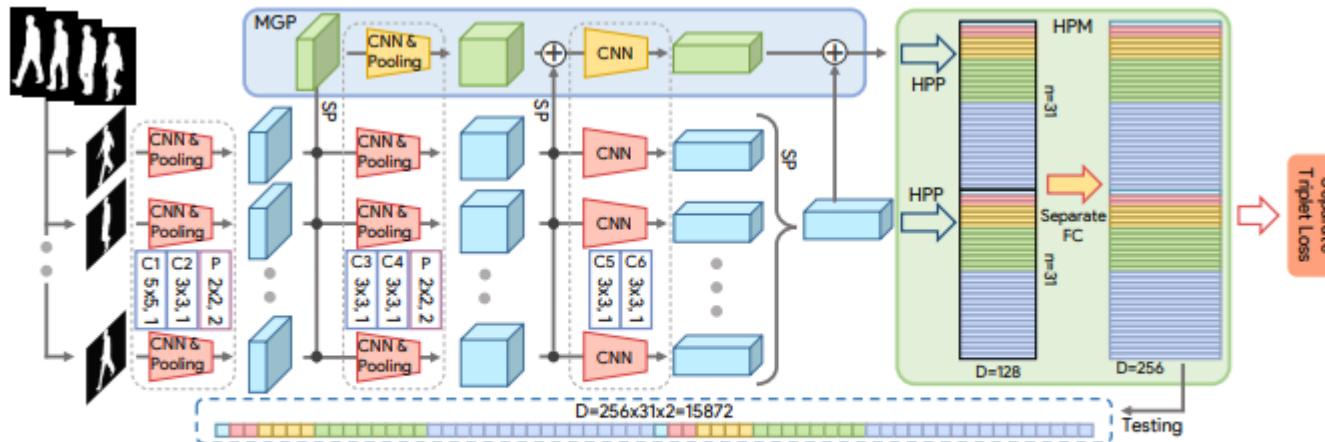


Figure 2: The framework of GaitSet. 'SP' represents Set Pooling. Trapezoids represent convolution and pooling blocks and those in the same column have the same configurations which are shown by rectangles with capital letters. Note that although blocks in MGP have same configurations with those in the main pipeline, parameters are only shared across blocks in the main pipeline but not with those in MGP. HPP represents horizontal pyramid pooling (Fu et al. 2018).



# Human Biometric

- Techniques

- Gaits

- Performances

- Speed changes

- ❖ +/- 1 km/hour
        - ❖ +/- 2 km/hour
        - ❖ +/- 3 km/hour
        - ❖ +/- 4 km/hour

Degree of speed change (km/h)	Shape configuration	Without DCM (%)	With DCM (%)	Improvement (%)
0	$HSC_1$	98.67	99.33	1
1	$HSC_2$	96.80	98.00	1
2	$HSC_2$	85.00	92.50	8
3	$HSC_3$	75.33	85.33	10
4	$HSC_3$	66.00	83.00	17
5	$HSC_4$	64.00	84.00	20

Kusakunniran, W., Wu, Q., Zhang, J., & Li, H. (2012). Gait recognition across various walking speeds using higher order shape configuration based on a differential composition model. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 42(6), 1654-1668.



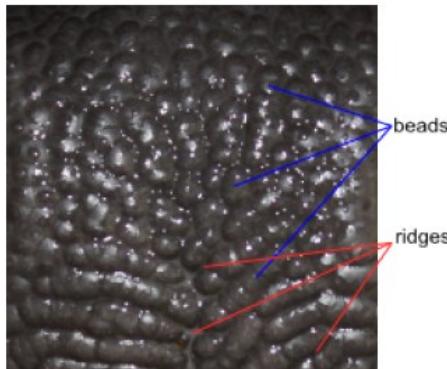
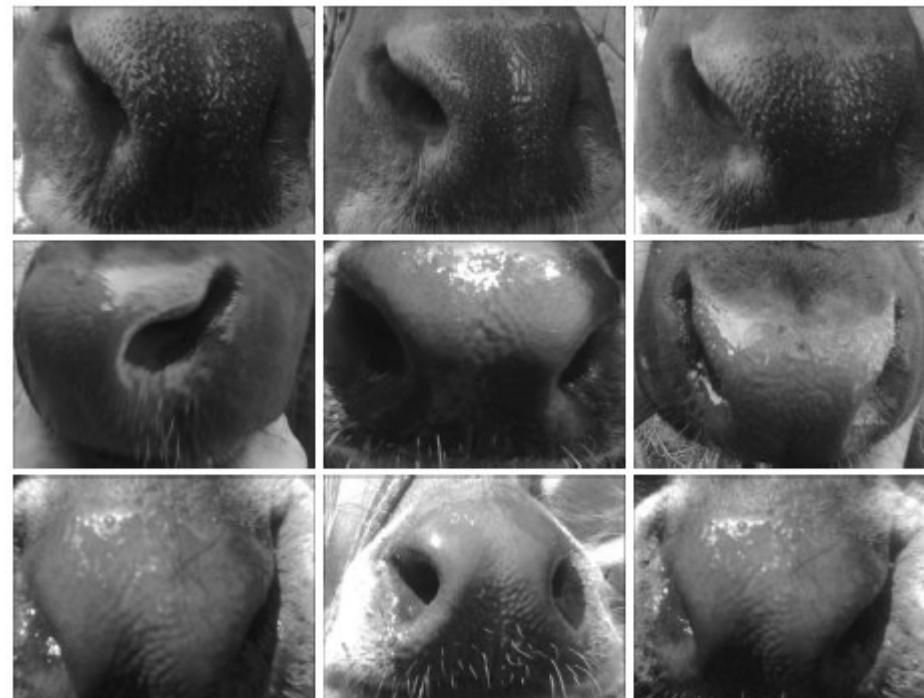
# Human Biometric

- Fusions (Multimodal Biometrics)
  - Fingerprint + Iris + Face
    - Reason ?
      - Missing of ridges patterns e.g. fisherman
      - Plastic surgery
      - Twin
    - Frameworks
      - Hierarchical approach
      - Score fusion
  - Gait + Face
    - Surveillance
      - Factors of distance and view



# Animal Biometric

- Cattles
  - Muzzles
  
- Dogs
  - Color
  - Face
  - Shape



A. Tharwat, T. Gaber, and A. E. Hassanien, “Two biometric approaches for cattle identification based on features and classifiers fusion,” International Journal of Image Mining, vol. 1, no. 4, pp. 342–365, 2015.



# Animal Biometric

- Benefits
  - Identify individuals
  - Prevent illegal trade
  - Disease surveillance/control
- Current Approaches
  - Ear tags
    - Loss
    - Swap
  - Microchips
    - Expensive
    - Difficult
    - Risky for human operators
    - Damage animals



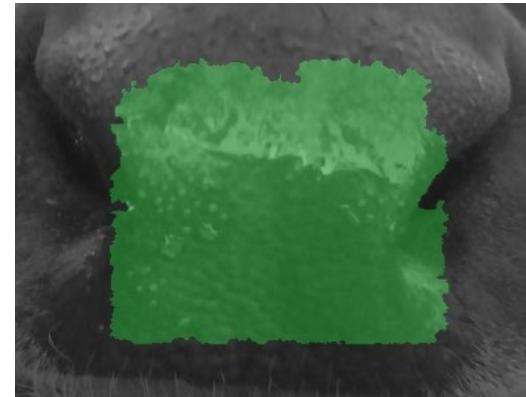
# Animal Biometric

Research	Year	Techniques	Data		Accuracy (%)
			Subjects	Images per subject	
Automatic Cattle Identification based on Muzzle Photo Using Speed-Up Robust Features Approach	2012	SURF	8	15	95
		USURF			100
A Cattle Identification Approach Using Live Captured Muzzle Print Images	2013	SIFT + RANSAC	15	7	93
Cattle Identification Based on Muzzle Images Using Gabor Features and SVM Classifier	2014	Gabor + LDA + SVM	31	7	100
Cattle Identification using Muzzle Print Images based on Texture Features Approach	2014	LBP + KNN	31	7	100
		LBP + SVM			100
Automatic cattle muzzle print classification system using multiclass support vector machine	2015	Box counting + MSVM	52	20	100
Muzzle-based Cattle Identification using Speed up Robust Feature Approach	2015	SURF + SVM	31	7	100
Cattle Identification Using Segmentation-based Fractal Texture Analysis and Artificial Neural Networks	2016	ANN	52	20	100
Muzzle point pattern based techniques for individual cattle identification	2016	Gaussian Pyramid + SURF + LBP	500	6	94
Automatic Cattle Identification based on Fusion of Texture Features Extracted from Muzzle Images	2018	LBP + Gabor + Sub-image + SVM	31	7	100



# Animal Biometric

- Challenges
  - Live scan
- Overall process
  - Image enhancement
  - Face localization
  - Muzzle ROI selection
  - Feature extraction
  - Classification





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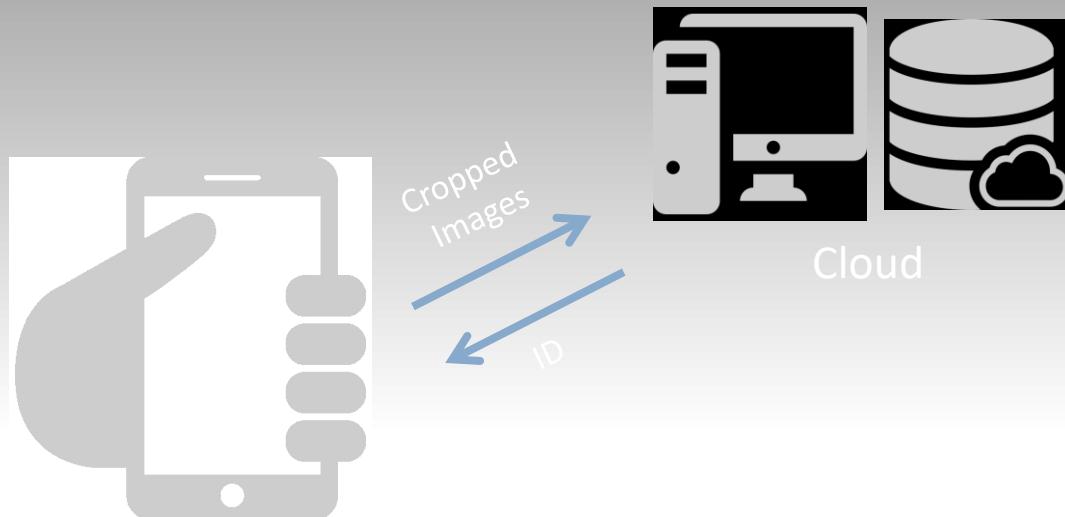
# In Fields





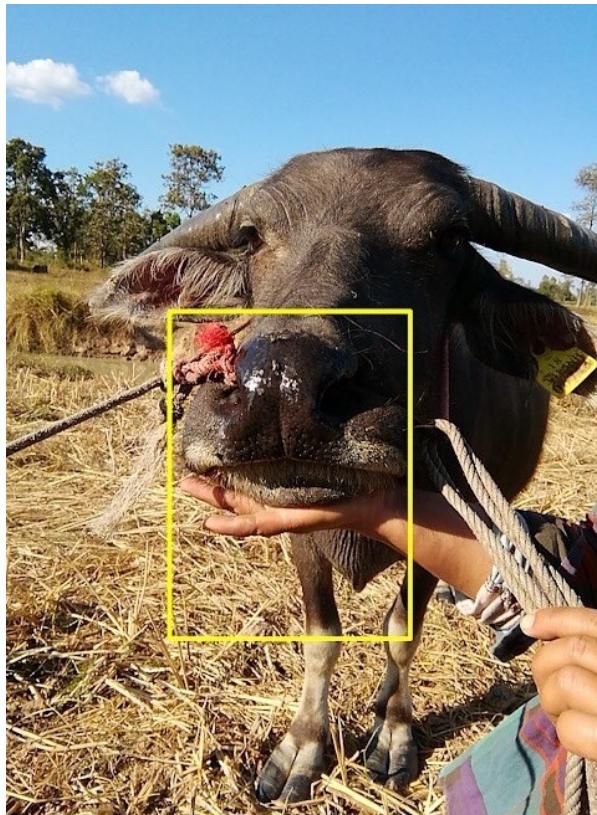
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# Cattle Identification by muzzle images



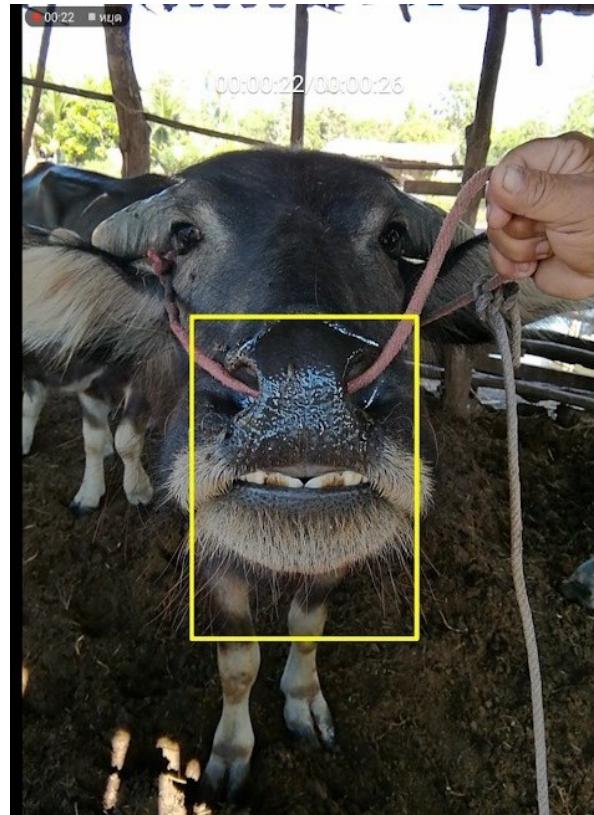


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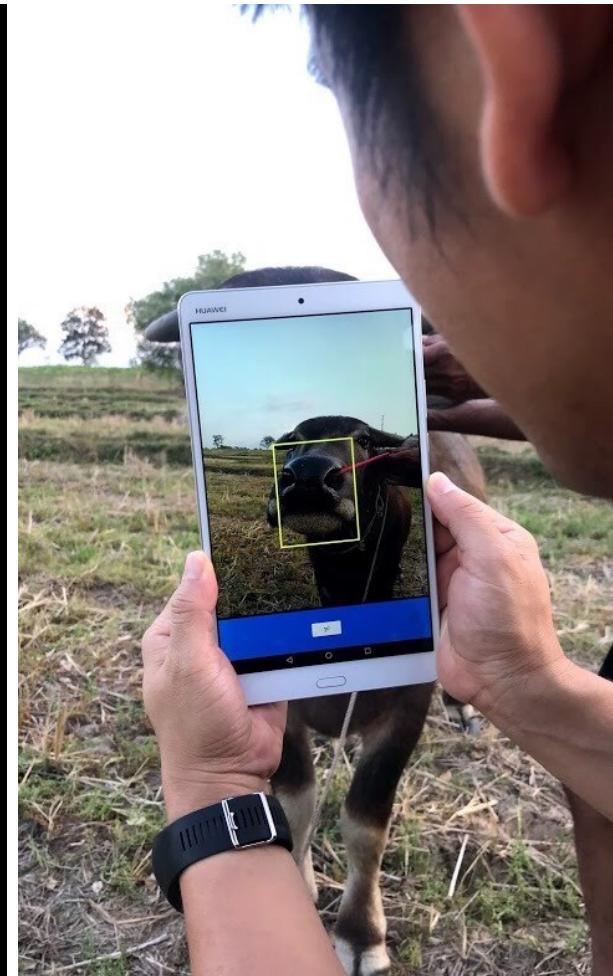
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# Our Works

# of Subjects	# of images each	Accuracy
431	10 (10-fold cross-validation)	95%
408	20 (10-fold cross-validation)	96%



# Medical Imaging

- DR in retinal image
  - Fusion of instance-learning and supervised-learning
- Segmentation of outer wall of Abdominal Aortic Aneurysm in CT-scan
  - VNS between gradient and intensity searching spaces

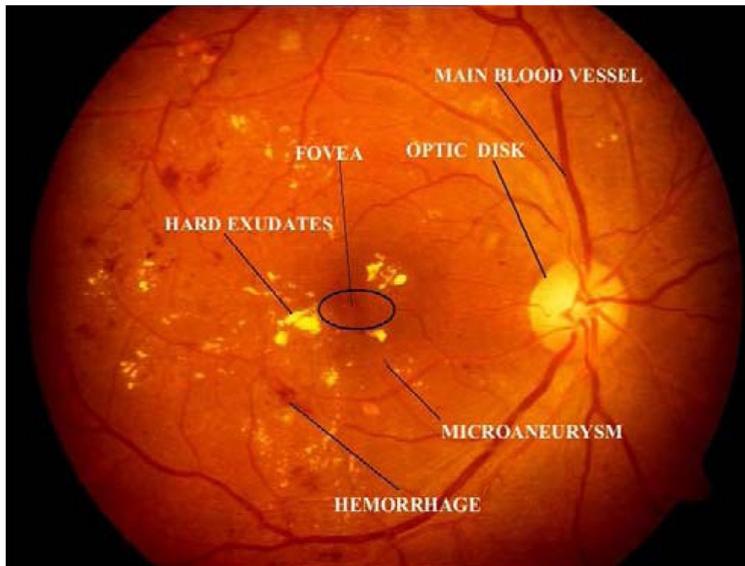


# DR Detection

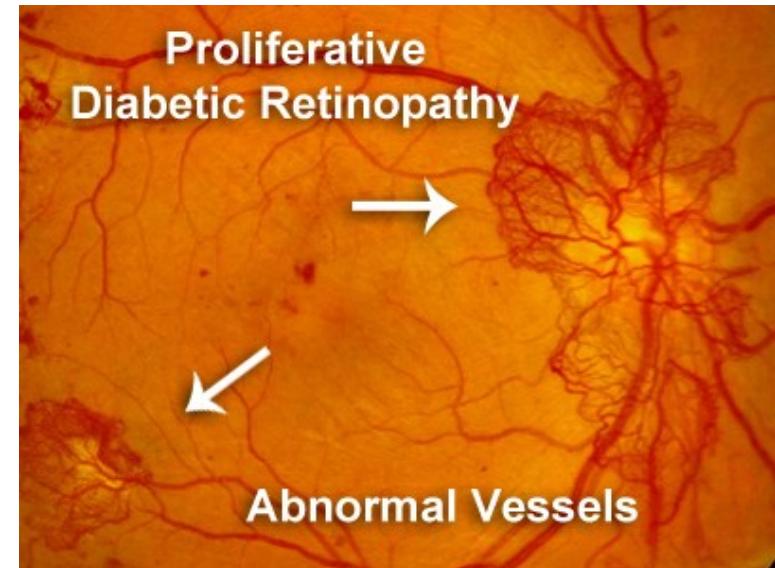
- Mild non-proliferative
  - At least one **microaneurysm**
- Moderate non-proliferative
  - Numerous **microaneurysms**
  - **Haemorrhages**
  - **Cotton wool spots**
  - **Hard exudates**
  - Small amount of **venous beading**
- Severe non-proliferative
  - Exists one of the following characteristics
    - A large amount of **microaneurysms** and **haemorrhages**, in all four quadrants
    - A **venous beading**, in two or more quadrants
    - Intra-retinal **microvascular abnormalities**, in at least one quadrant
- Proliferative
  - **New blood vessels** which will be abnormal, fragile, bent and tortuous/twisted
  - Result in severe vision **loss and the blindness**



# DR Detection



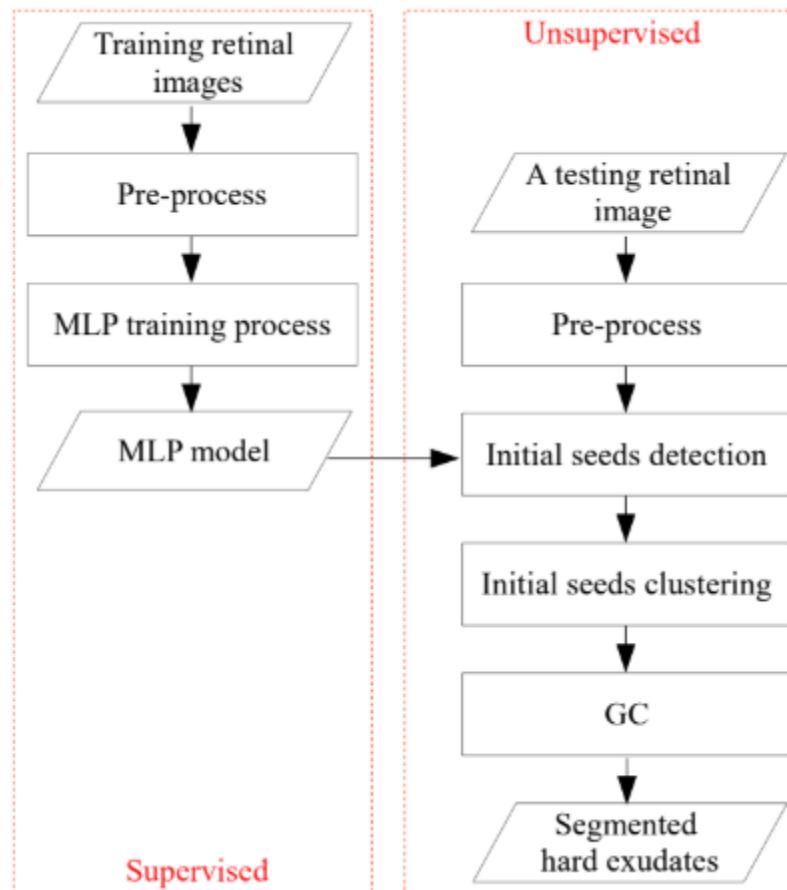
Pachiyappan , Das , Vsp Murthy , Tatavarti R. Automated diagnosis of diabetic retinopathy and glaucoma using fundus and OCT images. *Lipids in Health and Disease.* 2012 June; 11(1).



Retina Vitreous Associates of Florida. [Website].; 2018 [cited 2018 October 23. Available from: [http://retinavitreous.com/diseases/dm\\_pdr.php](http://retinavitreous.com/diseases/dm_pdr.php).



# DR Detection

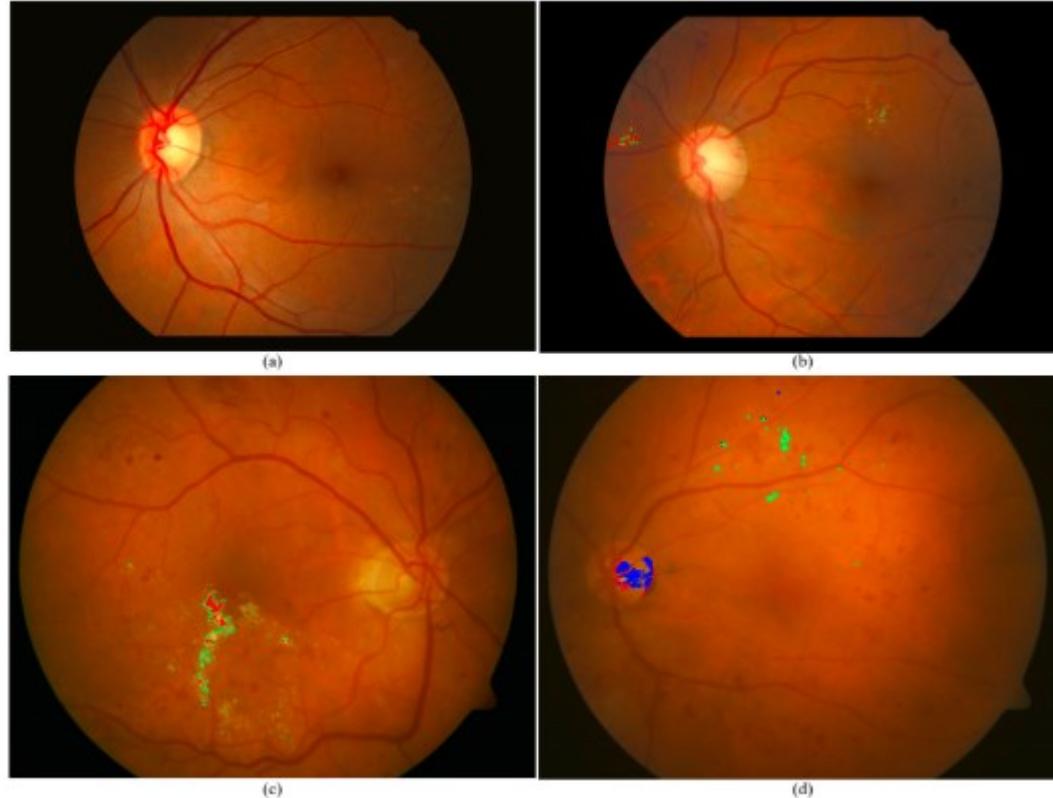


W. Kusakunniran, Q. Wu, P. Ritthipravat, J. Zhang, Hard Exudates Segmentation based on Learned Initial Seeds and Iterative Graph Cut, Computer Methods and Programs in Biomedicine (CMPB), 158: 173-183, May 2018, DOI: 10.1016/j.cmpb.2018.02.011



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# DR Detection

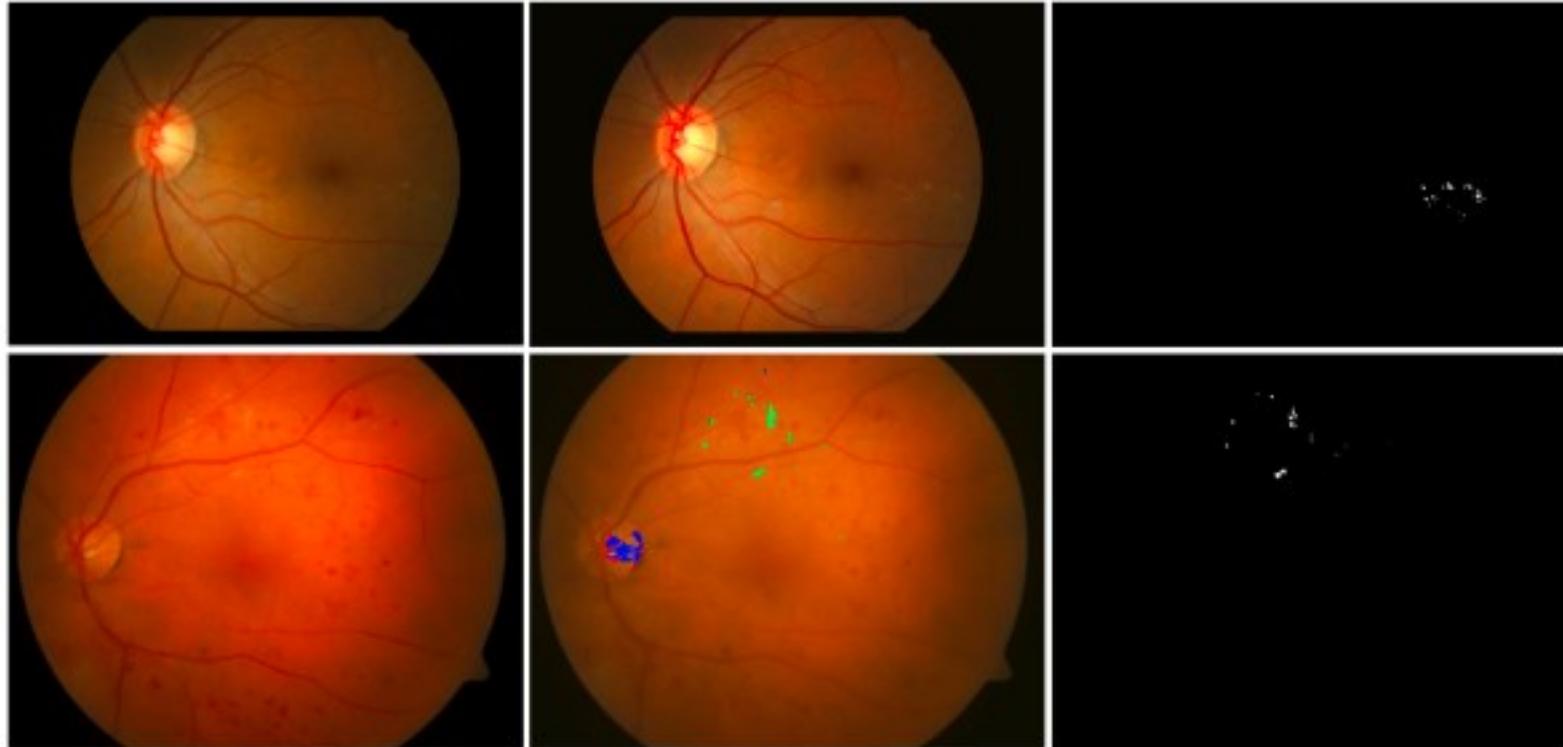


W. Kusakunniran, Q. Wu, P. Ritthipravat, J. Zhang, Hard Exudates  
Segmentation based on Learned Initial Seeds and Iterative Graph Cut,  
Computer Methods and Programs in Biomedicine (CMPB), 158: 173-  
183, May 2018, DOI: 10.1016/j.cmpb.2018.02.011



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# DR Detection

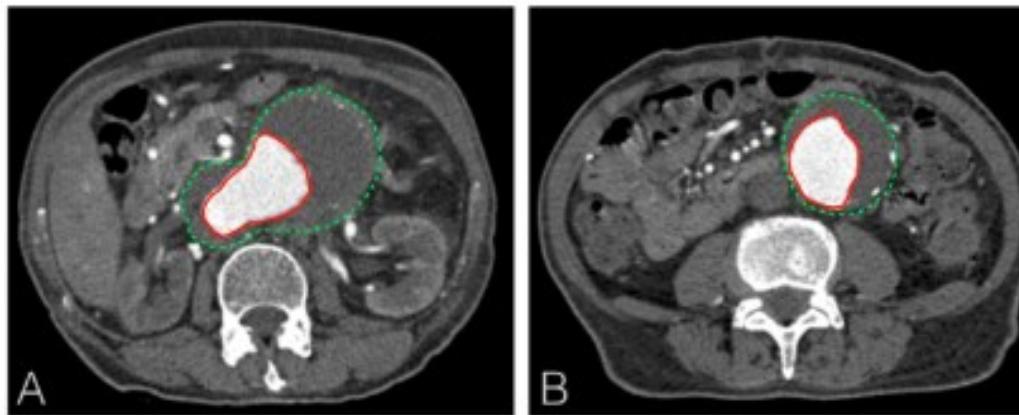


W. Kusakunniran, Q. Wu, P. Ritthipravat, J. Zhang, Hard Exudates  
Segmentation based on Learned Initial Seeds and Iterative Graph Cut,  
Computer Methods and Programs in Biomedicine (CMPB), 158: 173-  
183, May 2018, DOI: 10.1016/j.cmpb.2018.02.011

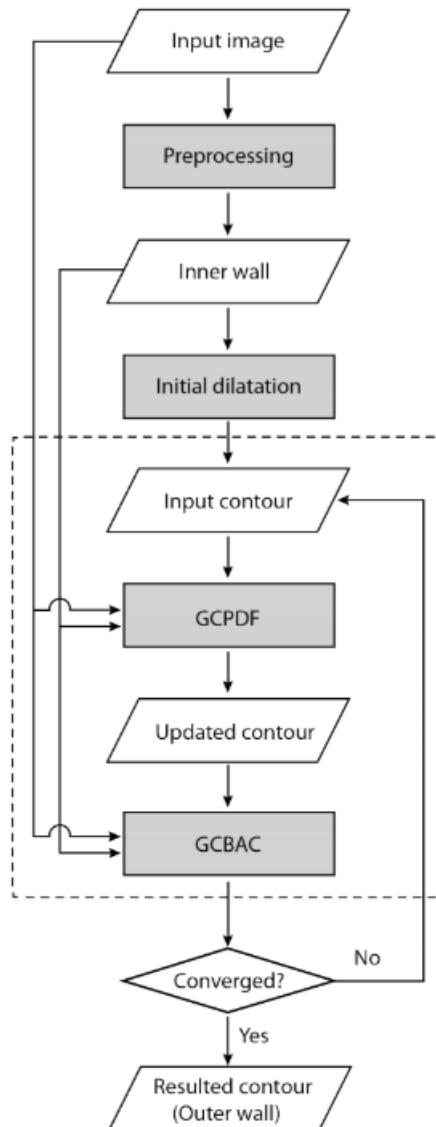


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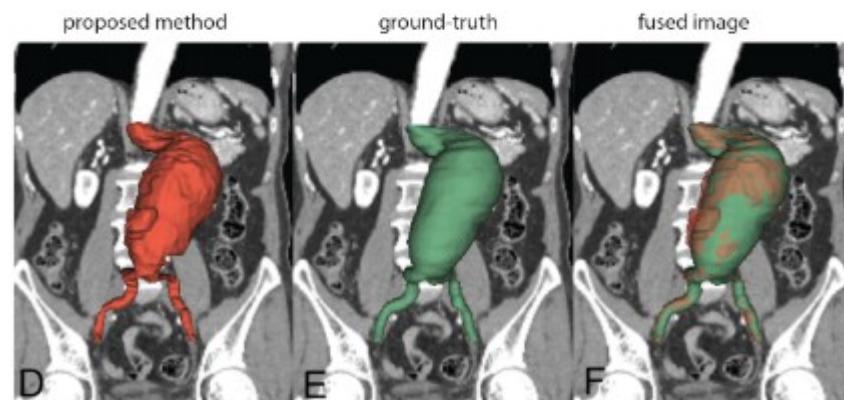
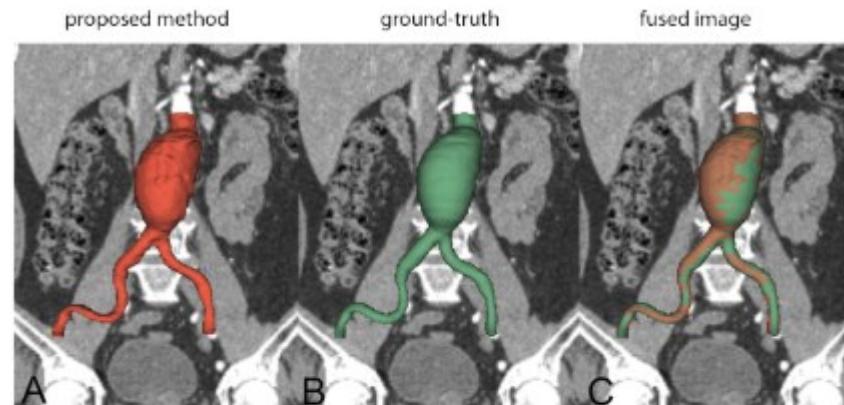
# Segmentation of Abdominal Aortic Aneurysm (Outer wall)



T. Siriapisith, W. Kusakunniran, P. Haddawy, Outer Wall Segmentation of Abdominal Aortic Aneurysm by Variable Neighborhood Search through Intensity and Gradient Spaces, Journal of Digital Imaging (JDIM), 31(4): 490-504, August 2018, DOI: 10.1007/s10278-018-0049-z



# Segmentation of Abdominal Aortic Aneurysm (Outer wall)



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# Segmentation of Abdominal Aortic Aneurysm (Outer wall)

**Table 1** Quantitative evaluation of aortic aneurysm segmentation compared with standard reference (ground truth) using dice similarity coefficient (DSC), based on our dataset. AC = active contour without edges, DRLSE = distance regularized level set evolution, GC = graph cut, GCBAC = graph cut based active contour, GCPDF = graph cut with probability density function.

	The proposed method	AC[34]	DRLSE[35]	GC[27]	GCBAC[28]	GCPDF
Easy case	94.69±3.54	52.24±9.84	59.92±10.54	68.71±19.35	64.86±16.83	66.23±11.51
Difficult case	93.37±5.45	48.94±10.46	59.48±11.17	70.12±14.63	64.26±16.33	63.62±12.00
Mean	93.60±4.97	50.59±10.24	59.70±10.86	69.48±16.87	64.53±16.49	64.81±11.80

**Table 2** Quantitative evaluation of aortic aneurysm segmentation compared with standard reference (ground truth) using jaccard similarity coefficient (JSC), based on our dataset. AC = active contour without edges, DRLSE = distance regularized level set evolution, GC = graph cut, GCBAC = graph cut based active contour, GCPDF = graph cut with probability density function.

	The proposed method	AC[34]	DRLSE[35]	GC[27]	GCBAC[28]	GCPDF
Easy case	90.11±5.97	35.99±9.70	43.64±11.53	55.62±23.01	50.12±17.75	50.62± 13.28
Difficult case	87.99±6.24	33.04±9.56	43.24±11.41	55.88±17.34	49.44±17.91	47.77±12.96
Mean	88.33±7.67	34.53±9.69	43.44±11.47	55.77±20.02	49.75±17.76	49.06±13.13



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# Segmentation of Abdominal Aortic Aneurysm (Outer wall)

## A General Approach to Segmentation in CT Grayscale Images using Variable Neighborhood Search

Thanongchai Siriapisith<sup>\*†</sup>, Worapan Kusakunniran<sup>†</sup>, Peter Haddawy<sup>†‡</sup>

<sup>\*</sup>Department Radiology, Faculty of Medicine Siriraj Hospital

Mahidol University, Bangkok, Thailand, 10700

<sup>†</sup>Faculty of Information and Communication Technology

Mahidol University, Nakhonpathom, Thailand, 73170

<sup>‡</sup>Bremen Spatial Cognition Center

University of Bremen, Germany

Email: thanongchai.sir@mahidol.ac.th Email: worapan.kun@mahidol.edu Email: peter.had@mahidol.ac.th

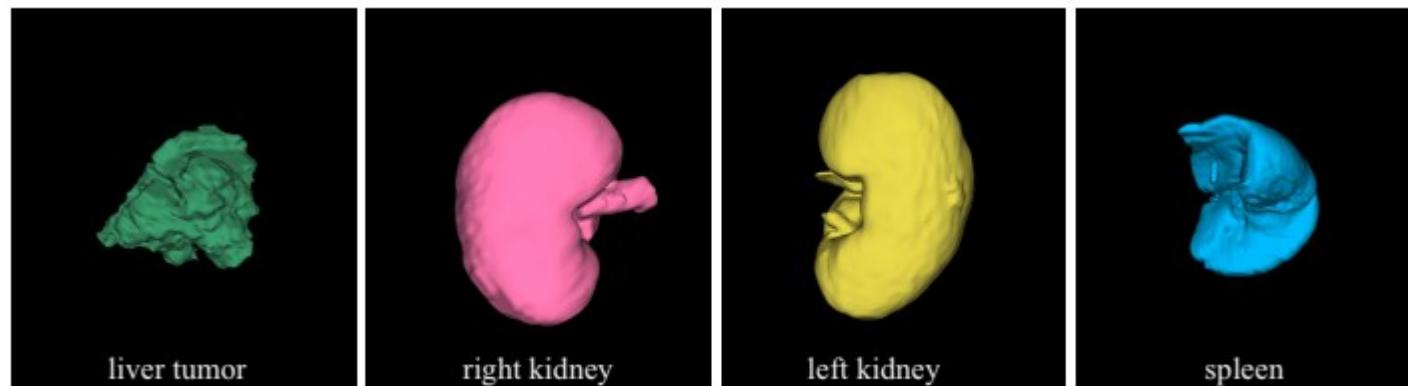


Fig. 4. Example of 3D models of the segmentation results of liver tumor, right kidney, left kidney and spleen.



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# Segmentation of Abdominal Aortic Aneurysm (Outer wall)

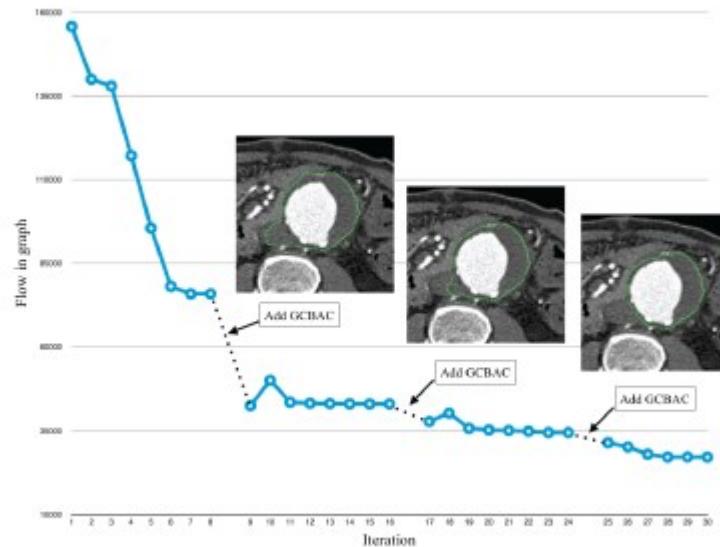
3D Segmentation of Exterior Wall Surface of Abdominal Aortic Aneurysm from CT images using Variable Neighborhood Search

Thanongchai Siriapisith<sup>a,b</sup>, Worapan Kusakunniran<sup>a,1</sup>, Peter Haddawy<sup>a,c</sup>

<sup>a</sup>*Faculty of Information and Communication Technology, Mahidol University,  
Nakhonpathom, Thailand*

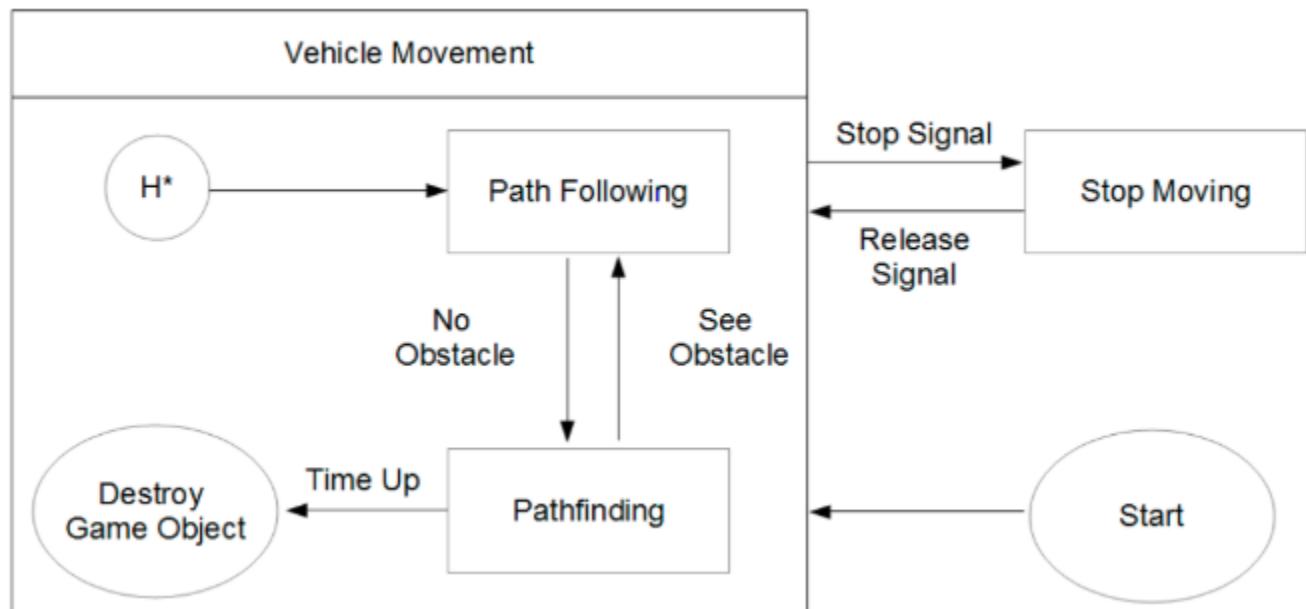
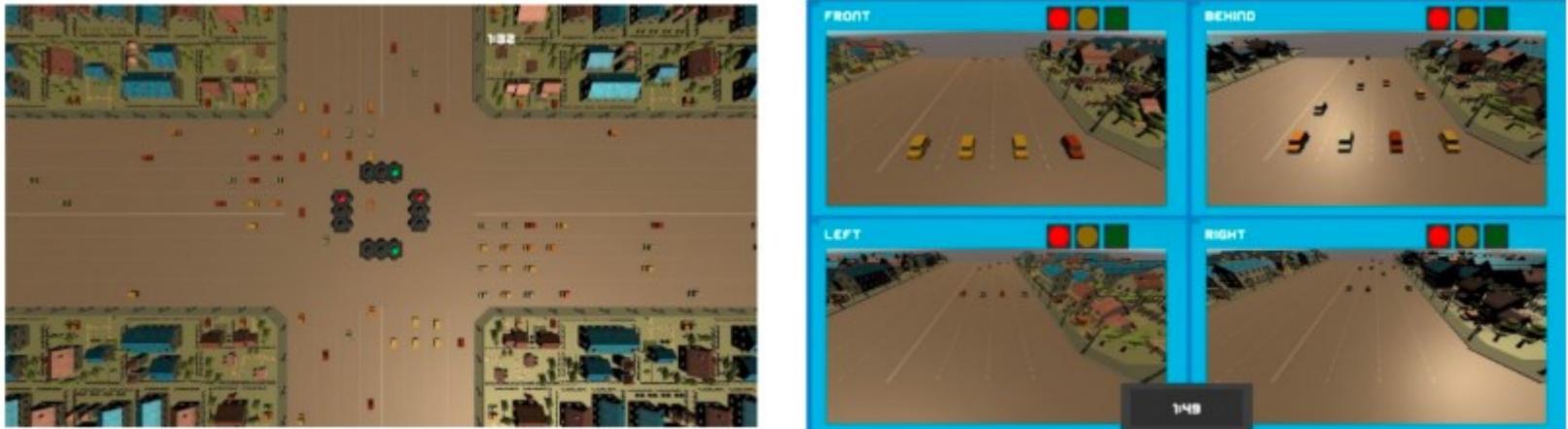
<sup>b</sup>*Faculty of Medicine Siriraj Hospital, Mahidol University, Bangkok, Thailand*

<sup>c</sup>*Bremen Spatial Cognition Center, University of Bremen, Bremen, Germany*





# Gaming Vision





# Gaming Vision

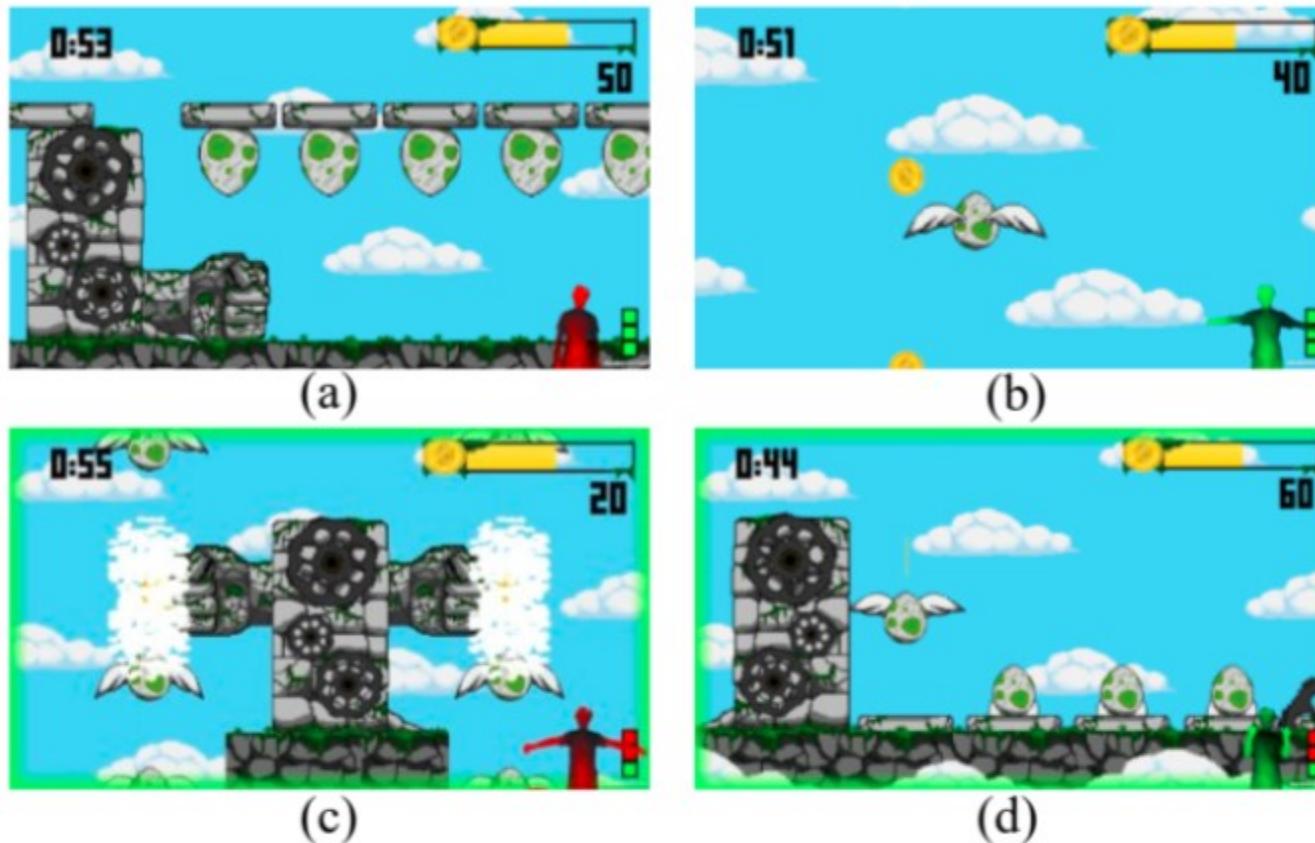
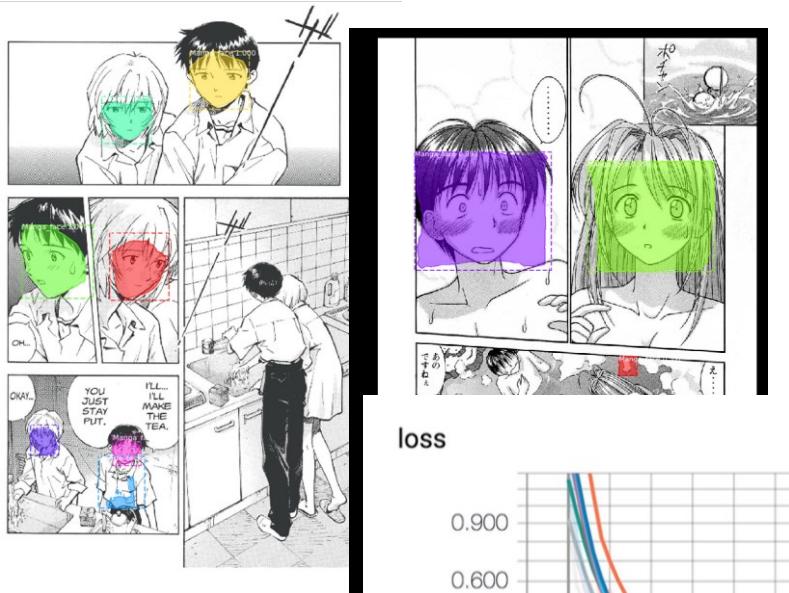


Fig. 1. Sample scenes of all four developed games. (a) The shoulder flexion game. (b) The shoulder abduction game. (c) The shoulder horizontal abduction game. (d) The elbow flexion/extension game.

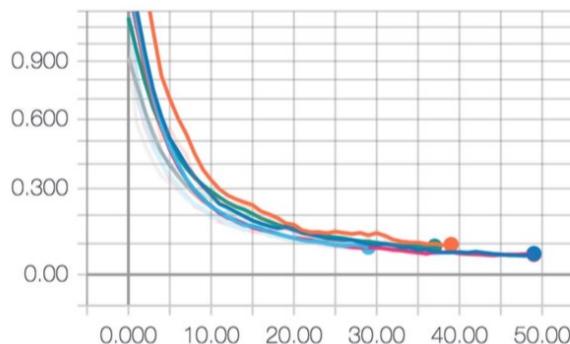


# Examples of using CNN

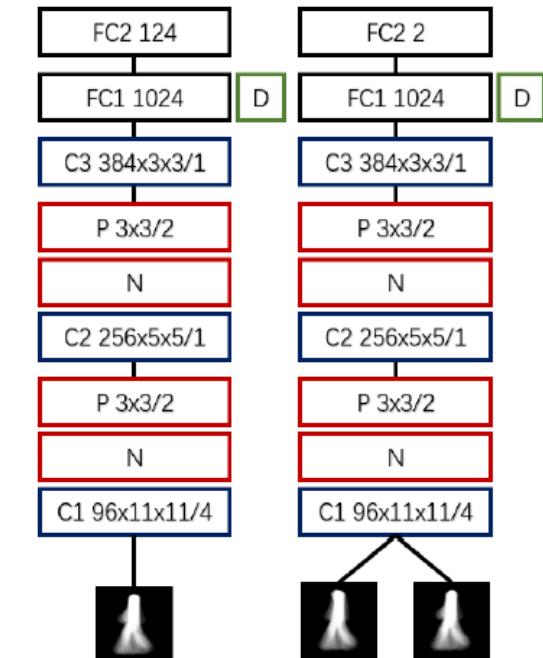
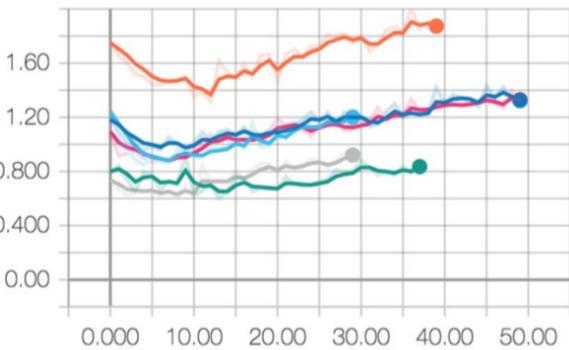
- Gait Recognition
- Manga Face Detection



loss



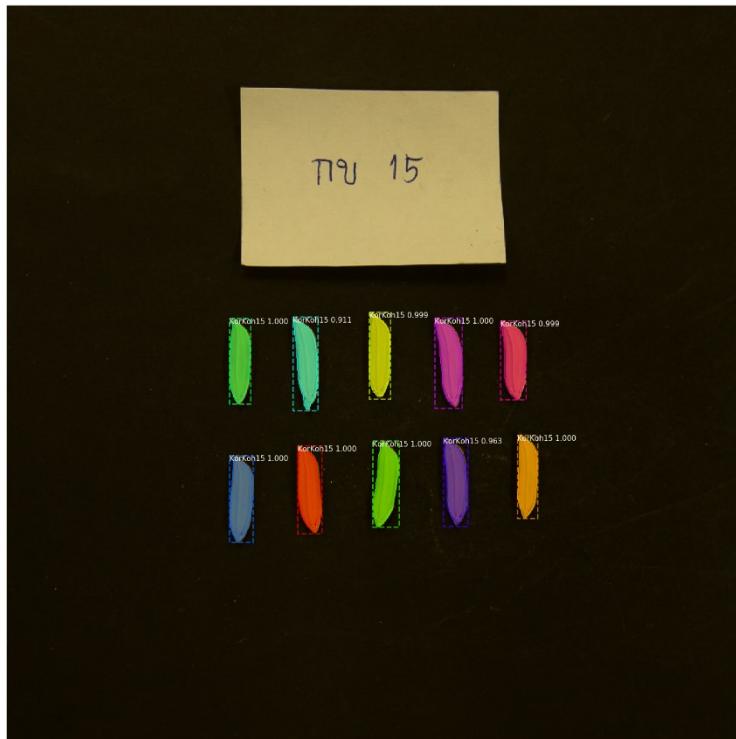
val\_loss





# Examples of using CNN

- Snow detection
- Rice grain classification





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# Supervising



Prof. Dr. Thanongchai Siriapisith  
Faculty of Medicine, Siriraj Hospital,



Suchakree Sawangwo  
Faculty of ICT, Mahidol University



Parintorn Pooyoi  
Faculty of ICT, Mahidol University



Poonyanut Thongsada  
Faculty of ICT, Mahidol University



Chawalit Aukkapinyo  
Faculty of ICT, Mahidol University



Punyanuch Borwarginn  
Faculty of ICT, Mahidol University



Sarattha Karnjanapreechakorn  
Faculty of ICT, Mahidol University



Anuttri Robkob  
Faculty of ICT, Mahidol University



Thanatchon Chaiviroonjaroen  
Faculty of ICT, Mahidol University



Isara Sasiwongsaroj  
Faculty of ICT, Mahidol University



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Thank you  
Q/A

Machine Vision and Information Transfer (MVIT)  
Research Group

