Image Informatics Tools in Support of Systems Biology

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Systems Biology and Location Proteomics

- All systems biology must be data driven
- Key to progress
 - identification of aspect that needs to be analyzed "ome-wide"
 - development of assays and automated analysis approaches
- Systems biology needs systematic information on highresolution subcellular location
 - Eventually, for every expressed protein for all cell types under all conditions
- Providing this information is the goal of Location Proteomics
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Automated Interpretation

- Traditional analysis of fluorescence microscope images has occurred by visual inspection
- Our goal over the past ten years has to been automate the interpretation, to yield better
 - Objectivity
 - Sensitivity
 - Reproducibility



Supervised Learning of High-Resolution Subcellular Location Patterns



The goal: Learn to recognize all major subcellular patterns

ER	giantin	gpp130	
			2D
LAMP	Mito	Nucleolin	Images of
		0:.	HeLa
			cells
Actin	TfR	Tubulin	DNA
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The Challenge

- Pixel-by-pixel or region-by-region matching will not work for cell patterns because different cells have different shapes, sizes, orientations
- Organelles/structures within cells are not found in fixed locations
- Instead, describe each image numerically and compare the descriptors





Feature-based, Supervised learning approach

- Create sets of images showing the location of many different proteins (each set defines one class of pattern)
- 2. Reduce each image to a set of numerical values ("features") that are insensitive to position and rotation of the cell
- 3. Use machine learning methods to "learn" how to distinguish each class using the features

 Boland et al 1996; 1997; 1998;

 Boland & Murphy 2001; Huang &

 2007 TCNP All Hands Meeting
 Murphy 2004



Boland et al 1997; 1998; Boland & Murphy 2001; Huang & Murphy 2004



Murphy et al 2000; Boland & Murphy 2001; Huang & Murphy 2004

2D Classification Results

True		Output of the Classifier								
Class	DNA	ER	Gia	Gpp	Lam	Mit	Nuc	Act	TfR	Tub
DNA	99	1	0	0	0	0	0	0	0	0
ER	0	97	0	0	0	2	0	0	0	1
Gia	0	0	91	7	0	0	0	0	2	0
Gpp	0	0	14	82	0	0	2	0	1	0
Lam	0	0	1	0	88	1	0	0	10	0
Mit	0	3	0	0	0	92	0	0	3	3
Nuc	0	0	0	0	0	0	99	0	1	0
Act	0	0	0	0	0	0	0	100	0	0
TfR	0	1	0	0	12	2	0	1	81	2
Tub	1	2	0	0	0	1	0	0	1	95

Overalloraccuracy = 92%

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Human Classification Results

True		Output of the Classifier								
Class	DNA	ER	Gia	Gpp	Lam	Mit	Nuc	Act	TfR	Tub
DNA	100	0	0	0	0	0	0	0	0	0
ER	0	90	0	0	3	6	0	0	0	0
Gia	0	0	56	36	3	3	0	0	0	0
Gpp	0	0	54	33	0	0	0	0	3	0
Lam	0	0	6	0	73	0	0	0	20	0
Mit	0	3	0	0	0	96	0	0	0	3
Nuc	0	0	0	0	0	0	100	0	0	0
Act	0	0	0	0	0	0	0	100	0	0
TfR	0	13	0	0	3	0	0	0	83	0
Tub	0	3	0	0	0	0	0	3	0	93
$\frac{Overallo}{a GGULLAGY} = \frac{83\%}{10}$										10

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Computer vs. Human





Conclusions (1996-2004)

- Automated classification of subcellular patterns possible without colocalization
- Accuracy better than visual examination
 - Similar for basic patterns
 - Better for similar patterns
- 3D images give better accuracy than 2D
 >> SLFs capture essence of patterns



Unsupervised Learning to Identify High-Resolution Protein Patterns



Location Proteomics

Tag many proteins

 We have used CD-tagging

 (developed by Jonathan Jarvik and Peter Berget): Infect population of cells with a retrovirus carrying DNA sequence that will "tag" in a random gene



Jarvik et al 2002

Isolate separate clones, each of which produces express one tagged protein

Use RT-PCR to identify tagged gene in each clone

 Collect many live cell images for each clone using spinning disk confocal fluorescence microscopy











Predominantly Nuclear Proteins with Some Punctate Cytoplasmic Staining

	Ieton
	SIM
	sm b+w uniform
Rib+Unk	sm iform
суторноцк	Sm
	Sm
	iform
	SM SM
	sm+w nucleus



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Generative Models for Subcellular Location Patterns



Need

- How do we communicate results of clustering patterns?
- Show all images from a given cluster?
 - Long download
 - No ability to generalize
- Proposal: Use generative models





Nuclear Shape - Medial Axis Model



Synthetic Nuclear Shapes



Synthetic nuclei generated by learned model





Cell Shape Description: Distance Ratio



 $\frac{d_1 + d_2}{d_2}$

Capture variation as a principal components model



Examples of natural variation in cell shape





Example cell boundary generated from learned model





Modeling Vesicular Organelles

Original image and fitted Gaussians of increasing complexity





Object Positions



 $=\frac{d_2}{d_1+d_2}$



Synthesized Images



Lysosomes

Endosomes



Synthesized Images



Mitochondria

Nucleoli



Model Distribution

- Generative models provide better way of distributing what is known about "subcellular location families" (or other imaging results, such as illustrating change due to drug addition)
- Have initial XML design for capturing the models for distribution
- Have portable tool for generating images from the model



Generation Process





Generating Multiple Distributions for Simulations





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Combining Models for Cell Simulations



The Protein Subcellular Location Image Database (PSLID)



Huang et al 2002; Huang et al 2007

PSLID: Protein Subcellular Location Image Database

- A publicly accessible image database at http://pslid.cbi.cmu.edu
 - Version 3 released February 2, 2007
 - 2D and 3D images (single cell regions defined)
 - Two cell types, HeLa and 3T3
 - Over 120,000 images/3000 unique fields/14,000 cells
 - 111classes; 55 known proteins; 11 targeting mutants of a single protein
 - Programmatic search via URL (SOAP in the works)



Huang et al 2002; Huang et al 2007

PSLID: Protein Subcellular Location Image Database

- A downloadable open source system for creating local databases
 - Version 3 of software released February 13, 2007
 - Focused on subcellular pattern analysis
 - SLF features integrated into database
 - Integrated comparison, classification, clustering tools
 - Designed for high-throughput microscopy
 - Interface to OME in the works
 - Large ITR project with UCSB for distributed system

See poster by Estelle Glory



External search

- The programmable search has the following format: http://pslid.cbi.cmu.edu/public3/search.j sp?arguments
- The following search arguments are supported:
- protein=protein name
- cell_type=cell type



External search

http://pslid.cbi.cmu.edu/public3/search.j sp?protein=calponin-2



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http://pslid.cbi...otein=calponin-2 emp7_710B35DB64C10A8CF21...

Search results for Image Type: 2D Static, Target: calponin-2

10 regions returned (30 regions shown) from the query.

View the summary of set temp8_710B35DB64C10A8CF219992B3A193B57.

Click $\stackrel{\frown}{\uparrow}$ besides a given image to retrieve similar images in the database.

	Image	Cell Name	Organism	Segmenter	Experiment	Protocol	Target	Microscopy & Filter
9	Region 68249	3T3	Mus musculus	External	<u>Cyto039</u>	GFP_Live	<u>Calponin-2</u>	<u>Olympus IX500</u>
9	Region 68280	3T3	Mus musculus	External	<u>Cyto039</u>	GFP_Live	<u>Calponin-2</u>	<u>Olympus IX500</u>
9	Region 68311	3T3	Mus musculus	External	<u>Cyto039</u>	GFP_Live	<u>Calponin-2</u>	<u>Olympus IX500</u>
9	Region 68342	3T3	Mus musculus	External	<u>Cyto039</u>	GFP_Live	<u>Calponin-2</u>	<u>Olympus IX500</u>
9	Region 68373	3T3	Mus musculus	External	<u>Cyto039</u>	<u>GFP_Live</u>	<u>Calponin-2</u>	<u>Olympus IX500</u>
9	Region 68404	3T3	Mus musculus	External	<u>Cyto039</u>	GFP_Live	Calponin-2	<u>Olympus IX500</u>
9	Region 68435	3T3	Mus musculus	External	<u>Cyto039</u>	GFP_Live	Calponin-2	<u>Olympus IX500</u>
0		3T3	Mus musculus	External	Cyto039	GFP Live	Calponin-2	Olympus IX500

Image Content-based Retrieval and Interpretation of Micrographs from On-line Journal Articles

The Subcellular Location Image Finder (SLIF)



Ultimate Goal of the field

- Machine understanding of biological journal articles (text and image)
- Criteria for success: Turing test have machine be able to answer questions about an article as well as a human scientist



Intermediate Goal

- Extract information from combination of text and any kind of image in biological journal article
- Criteria for success: Achieve high precision and recall for extracted assertions (compared to expert scientist)



Immediate Goal (SLIF)

- Extract information about subcellular location from captions and figures containing fluorescence microscope images in biological journal articles
- Criteria for success: Achieve high precision and recall for extracted assertions (compared to expert scientist)



State of art: Bio Journal Information Extraction

- A number of systems to index literature via extracted terms
- A few systems to index image content in literature
- A few systems for document classification



Overview: Image processing tasks

into "panels"

Detect & remove **annotations**

Classify panels

Find scale bars

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Overview: Text processing tasks

• Find *entity names* in text, and *panel labels* in text and the image.

• *Match* panels labels in text to panel labels on the image.

• Associate entity names to textual panel labels using *scoping* rules.

Figure 1. (A) Single confocal optical section of BY-2 cells expressing U2E 0 GFP, double labeled with GFP (left panel) and autoantibody against p80 coilin (right panel). Three nuclei are shown, and the bright GFP spots colocalize with bright foct of anti-coilin labeling. There is some labeling of the cytoplasm by anti-p80 coilin. (B) Single confocal optical section of BY-2 cells expressing U2B 0 -GFP, double labeled with GFP (left panel) and 4G3 antibody (right panel). Three nuclei are shown. Most coiled bodies are in the nucleoplasm, but occasionally are seen in the nucleolus (arrows). All coiled bodies that contain U2B 0 also express the U2B 0-GFP fusion. Bars, 5 m m. Movement of Coiled Bodies Vol. 10, July 1999 2299

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Linking to SLIF from another website

- Queries against the database can be made from outside the website using http://slif.cbi.cmu.edu/SLIF/search.jsp?arguments
- The arguments are:
 - protein=<protein name>
 - Ievel=figure OR level=panel
 - type=FMI (NOTE that BOTH level and type must be present if either is present)
 - pixel_size_lo=<lower bound>
 - pixel_size_hi=<upper bound> (NOTE that both upper and lower bounds must be specified)
 - location=<subcellular location>

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SOAP interface - query DTD

<!ELEMENT slif query (protein name, fmi level, pixel res lower bound, pixel_res_upper_bound, subcellular location)> <!ELEMENT protein name (#PCDATA)> <!ELEMENT fmi level EMPTY> <!ATTLIST fmi_level figure_or_panel (figure|panel) #REQUIRED> <!ELEMENT pixel res lower bound (#PCDATA)> <!ELEMENT pixel res upper bound (#PCDATA)> <!ELEMENT subcellular location (#PCDATA)>
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SOAP interface - results DTD

<!ELEMENT slif result (slif row*)> <!ELEMENT slif_row (caption, figure url, panel_url, protein_name, cell_name, subcellular_location, pixel_resolution)> <!ELEMENT caption (#PCDATA)> <!ELEMENT figure_url (#PCDATA)> <!ELEMENT panel url (#PCDATA)> <!ELEMENT protein_name (#PCDATA)> <!ELEMENT cell_name (#PCDATA)> <!ELEMENT subcellular_location (#PCDATA)> Carnegie Mellon

Subcellular Location Image Finder



Subcellular Location Image Finder

SLIF (Subcellular Location Image Finder) automatically extracts information about protein subcellular locations from figure-caption pairs in biological literature. SLIF separates figures into panels and decides which panels contain fluorescence microscope images (FMI). It applies image processing methods to analyze the FMI and extract a quantitative description of the localization patterns they display. The associated captions are also processed to identify which portions of the caption refer to which panels and to identify the names of proteins contained in the captions. The results of this analysis are stored in the SLIF database.

Our long-term goal is to develop a large library of annotated and analyzed fluorescence microscope images, in order to support data-mining.

PNAS, version 3.0

The current version of the database contains records for 15180 papers from volumes 94-99 of the Proceedings of the National Academy of Sciences (USA), generously made available by the Academy for demonstration purposes.

BioMed Central, version 1.0

Due for release March 5, 2007

Pubmed Central, version 1.0

The database will be expanded shortly to include all open access articles in Pubmed Central, including BMC papers but not PNAS papers (approximately 45,000 as of 31 December 2007).

A service of the Robert F. Murphy laboratory Departments of <u>Biological Sciences</u>, <u>Biomedical Engineering</u>, and <u>Machine Learning</u> and <u>Center for Bioimage Informatics</u> <u>Carnegie Mellon University</u>, Pittsburgh, Pennsylvania, U.S.A.

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Conclusions

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- Methods well worked out for classifying and learning protein patterns - better than visual examination
- Temporal information improves discrimination
- Progress on decomposing complex patterns and generative models
 - High-resolution, reliable data for bottom-up systems modeling
- Graphical models provide improved classification of single cells in fields (and potentially tissues)
- Image database integrated with interpretation tools (PSLID)
- Information extractor for online text and images (SLIF)



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The Future of Subcellular Pattern Analysis





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Other subcellular location projects

- O'Shea group Yeast
 - GFP-tagged cDNAs

Automated Analysis - see poster by Shann-Ching Chen

- GFP and DNA images with some additional markers
- Pepperkok group human (MCF7 cells)
 - GFP-tagged cDNAs
 - GFP and DNA images
- Uhlen group (Protein Atlas) human
 - Immunohistochemistry with monospecific antibodies
 - DAB and hematoxylin images
 - Fixed tissues
- Schubert group (MELK technology)
 - Cycles of immunofluorescence, imaging and bleaching
- Fixed tissues Carnegie Mellon

Orthogonal data sources

- Cytochemical images like Protein Atlas (fixed cells, one color)
- Sequential multicolor immunofluorescence like MELK (fixed cells, many colors)
- GFP-tagged proteins (live cells, one to few colors)



How do we really analyze subcellular location?

- Classification and comparison good for focused questions but there are too many questions to ask
- Need intelligent (optimized) data collection: probabilistic methods to integrate available data, make predictions and suggest experiments



Human Cytome Project?

- Scope of problem argues for cooperation on grand scale
- New inference and synthesis methods



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Mission

The mission of the NCIBI is to facilitate scientific exploration of complex di currently feasible.

The Center develops and interactively integrates analytical and m appropriate molecular biology information from emerging experim

Collaboration with Dan Rines and Sumit Chanda (GNF San Diego) on high throughput location proteomics

> Aerospace -Corporation

> > 2007 TCNP All Hand Brian RAthey (UMich), CMU: Bob Marphy



Collaborations with Bill Mohler, Ian Moraru, Les Loew, Paul Campagnola (U Conn)

Collaboration with Badri Roysam (RPI) and Sally Temple (Albany Med Coll), Stem Cell Patterning and FARSIGHT system







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UM Press Release