

ENHANCING MICROBIAL INSIGHTS IN CANCEROUS TISSUE: UNVEILING THE HIDDEN MICROBIOME WITH AN ADVANCED HOST DEPLETION PIPELINE

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What is a microbiome?

microorganisms



tiny organisms living in all kinds of environments a community of microorganisms & their role within a specific environment, considering environmental conditions & interactions with each other

microbiome

Bacteria
Archaea
Fungi
Protists
Viruses

Human Gut Microbiome

Role of Gut Microbiota in Nutrition and Health



H. Flint Nat Rev Gastroenterol Hepatol (2012)

Human Gut Microbiome



Human Oral Microbiome

Components of the oral microbiome:











Viruses

Bacteria

Archaea

Fungi

Protozoa



Healthy microbiome (Eubiosis)





Unbalanced microbiome (Dysbiosis)

- Periodontitis/Caries & sequelae
- Endocarditis
- Atherosclerosis
- Alzheimer's disease
- Diabetes
- Head and neck cancer

A. Radaic Computational and Structural Biotechnology Journal (2021)



More bacteria reside in human body than the actual human cells The ratio of microbes to human cells is 1.3:1



Cancer



Human Microbiome

More bacteria reside in human body than the actual human cells The ratio of microbes to human cells is 1.3:1



D. Hanahan et al. Cell (2011); D. Hanahan Cancer Discovery (2022); D. Mager J Transl Med (2006)

Cancer

Human Microbiome



>15% of cancer cases worldwide are due to microbes



Helicobacter pylori (H. pylori)



Human papillomavirus (HPV)

Are there even more?

D. Hanahan et al. Cell (2011); D. Hanahan Cancer Discovery (2022); D. Mager J Transl Med (2006)

Are there microbes are in The Cancer Genome Atlas (TCGA)?

nature

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Article Published: 11 March 2020

Microbiome analyses of blood and tissues suggest cancer diagnostic approach

<u>Gregory D. Poore, Evguenia Kopylova, Qiyun Zhu, Carolina Carpenter, Serena Fraraccio, Stephen</u> Wandro, Tomasz Kosciolek, Stefan Janssen, Jessica Metcalf, Se Jin Song, Jad Kanbar, Sandrine Miller-Montgomery, Robert Heaton, Rana Mckay, Sandip Pravin Patel, Austin D. Swafford & Rob Knight 🖂

Nature 579, 567–574 (2020) Cite this article

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Disease type

Differences in microbiomes of **tumor tissue** across **cancer types**

Heatmap of classifier performance comparing one cancer type vs all others



Takeaway: Each cancer type has a unique microbiome

Differences in microbiomes of **tumor tissue** and **normal samples**

Heatmap of classifier performance comparing cancer vs normal



Differences in microbiomes between **stage I** and **stage IV** cancers

Heatmap of classifier performance comparing Stage I and stage IV cancers



Differences in microbiomes found in the blood of one cancer type vs. all others

> Takeaway: We can identify cancer type in patients using microbes found in the blood

> > (AUROC (ROC) and AUPR (PR))

Area under the curve												
			0.4		0.7		1.0	0				
	_	_		_	_	_		_				
0.91	0.46	0.87	0.44	0.88	0.45	0.86	0.48	0.87	0.51	BLCA		
1.00	0.97	1.00	0.97	1.00	0.96	0.98	0.91	1.00	0.93	LGG		
0.99	0.87	0.99	0.79	0.99	0.83	0.98	0.74	0.99	0.88	BRCA		
0.96	0.77	0.94	0.76	0.94	0.74	0.96	0.75	0.98	0.60	CESC		
1.00	0.94	0.99	0.86	0.99	0.93	0.98	0.91	0.98	0.65	COAD		
1.00	0.97	0.98	0.91	1.00	0.96	0.99	0.86	1.00	0.79	ESCA		
0.97	0.78	0.99	0.74	0.98	0.83	0.95	0.84	1.00	0.95	GBM		
0.93	0.75	0.92	0.70	0.91	0.68	0.90	0.66	0.96	0.75	HNSC		
1.00	0.81	0.98	0.58	0.97	0.62	0.99	0.45	0.99	0.67	KIRP		
1.00	0.89	0.99	0.74	0.99	0.78	1.00	0.91	0.99	0.57	LIHC		
0.98	0.85	0.99	0.88	0.97	0.82	0.98	0.81	0.93	0.58	LUAD		
1.00	0.95	1.00	0.91	0.99	0.82	1.00	0.98	1.00	0.95	ov		
0.99	0.93	0.99	0.87	0.98	0.85	0.99	0.90	1.00	0.93	PRAD		
0.99	0.85	0.99	0.92	0.99	0.91	0.99	0.88	0.97	0.55	READ		
0.97	0.85	0.98	0.89	0.90	0.90	0.98	0.91	0.99	0.79	SARC		
0.91	0.48	0.89	0.35	0.89	0.47	0.88	0.44	0.98	0.90	SKCM		
0.93	0.64	0.92	0.66	0.95	0.66	0.92	0.63	0.96	0.65	STAD		
0.96	0.84	0.94	0.71	0.93	0.65	0.95	0.81	0.97	0.83	THCA		
0.95	0.84	0.95	0.80	0.94	0.83	0.94	0.80	0.98	0.76	UCEC		
1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	UVM		
8	РВ	8	РВ	8	РВ	8	РВ	8	PR			
UB	AU	'n	AU	'n	AU	'n	AU	'n	AU			
A		LA				A		A				
FD		LCB		APCR		PCCB		MSE				

G. Poore et al. Nature (2020)

Cancer Microbiome



D. Hanahan Cancer Discovery (2022)

TCGA Microbiome + Fungal Reads



Previous Studies in Cancer Microbiome





Melanoma



Immunofluorescence for bacterial 16S rRNA



G. Sepich-Poore et al. *Science (*2021)

Future Directions of Cancer Microbiome



G. Sepich-Poore*, C. Guccione* et al. BioEssays (2022)



Define a pipeline that extracts microbial reads from whole genome sequencing samples of tumor tissue



Going from whole genome sequencing to microbial taxonomy



Computational Removal of Human Reads

 Human Reference: GRCh38

 Experimental Reads

Computational Removal of Human Reads



Computational Removal of Human Reads



Is there a better way to study the cancer microbiome?



Going from whole genome sequencing to microbial taxonomy





How can we check for contamination?







- Serially diluted positive controls
- Environmental swab controls
- Paraffin non-tissue controls
- Reagent 'blank' controls
- Biological samples



How can we check for contamination computationally?

- Determine relationships between samples using Robust Aitchison PCA (RPCA)
- Uses matrix completion so zero values do not influence the ordination

	Sample1	Sample2	Sample3	Sample4	Sample5
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Halobacteriales;f_;g_;s_haloarchaeon 3A1_DGR		0	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Halobacteriales;f_Haloarculaceae;g_Haloarcula;s_Haloarcula vallismortis		D	0 0) (0 0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Halobacteriales;f_Haloarculaceae;g_Halomicrobium;s_Halomicrobium mukohataei		D	0 0) (0 0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Halobacteriales;f_Haloarculaceae;g_Halorhabdus;s_Halorhabdus tiamatea		D	0 0) (0 0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Halobacteriales;f_Haloarculaceae;g_Halorientalis;s_Halorientalis persicus		D	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Halobacteriales;f_Haloarculaceae;g_Natronomonas;s_Natronomonas moolapensis		D	0	2 0	0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Halobacteriales;f_Halobacteriaceae;g_Halarchaeum;s_Halarchaeum acidiphilum		D	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Halobacteriales;f_Halobacteriaceae;g_Halobacterium;s_Halobacterium hubeiense		D	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Halobacteriales;f_Halobacteriaceae;g_Halobacterium;s_Halobacterium salinarum		D	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Halobacteriales;f_Halobacteriaceae;g_Halobacterium;s_Halobacterium sp. DL1		D	0 !	i (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Haloferacales;f_Haloferacaceae;g_Halobellus;s_Halobellus rufus		D	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Haloferacales;f_Haloferacaceae;g_Haloferax;s_Haloferax sp. SB29		D	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Haloferacales;f_Haloferacaceae;g_Halogeometricum;s_Halogeometricum pallidum		D	0 0) (00
${\tt k_Archaea; p_Euryarchaeota; c_Halobacteria; o_Haloferacales; f_Haloferacaceae; g_Haloplanus; s_Haloplanus natans}$		D	4 () (
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Haloferacales;f_Haloferacaceae;g_Haloquadratum;s_Haloquadratum walsbyi		D	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Haloferacales;f_Halorubraceae;g_Halopenitus;s_Halopenitus sp. DYS4		D	0 0) (0 0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Haloferacales;f_Halorubraceae;g_Halorubrum;s_Halorubrum californiense		D	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Haloferacales;f_Halorubraceae;g_Halorubrum;s_Halorubrum halophilum		0	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Haloferacales;f_Halorubraceae;g_Halorubrum;s_Halorubrum kocurii		D	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Haloferacales;f_Halorubraceae;g_Halorubrum;s_Halorubrum lipolyticum		D	0 0) (0 0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Haloferacales;f_Halorubraceae;g_Halorubrum;s_Halorubrum sp. BV1		D	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Haloferacales;f_Halorubraceae;g_Halorubrum;s_Halorubrum tebenquichense		D	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Natrialbales;f_Natrialbaceae;g_Halostagnicola;s_Halostagnicola sp. A56		D	0 0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Natrialbales;f_Natrialbaceae;g_Natrinema;s_Natrinema pellirubrum		D	0) (0
k_Archaea;p_Euryarchaeota;c_Halobacteria;o_Natrialbales;f_Natrialbaceae;g_Natronorubrum;s_Natronorubrum tibetense		D	0 0) (0
$k_archaea; p_Euryarchaeota; c_Methanomicrobia; o_Methanomicrobiales; f_Methanomicrobiaceae; g_Methanolacinia; s_Methanolacinia and the set of the set of$	44	3 256	5 227	5 1717	1337
$k_archaea; p_Euryarchaeota; c_Methanomicrobia; o_Methanosarcinales; f_Methanosarcinaceae; g_Methanosarcina; s_Methanosarcina matrix and the set of the s$		D	0 0) (0
k_Bacteria;p_;c_;o_;f_;g_;s_bacteria symbiont BFo2 of Frankliniella occidentalis		0	0) (0 0





Hartwig Medical Foundation (HMF) Dataset

- Contains over 5,000 metastatic human tissue samples
- Whole Genome Sequencing (WGS)
- Resulting in low-depth microbial reads



WGS of HMF data with **GRCh38 host depletion** shows splitting across sex in RPCA plot





Improved mapping of human Y chromosome reference





Released 2022



WGS of HMF data with **GRCh38 + T2T-CHM13 host depletion** shows no splitting across sex in RPCA plot



Male samples have many more reads removed using CHM13-T2T compared with females



Sex

Going from whole genome sequencing to microbial taxonomy



Using fecal microbiome studies to check our host depletion pipeline

Typical fecal microbiome study workflow:



Fecal samples are often publicly accessible because they are thought to contain such small amounts of human reads especially after host filtering

Current methods are not removing all the host data

nature microbiology

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Article Open Access Published: 15 May 2023

Reconstruction of the personal information from human genome reads in gut metagenome sequencing data

Yoshihiko Tomofuji ⊠, Kyuto Sonehara, Toshihiro Kishikawa, Yuichi Maeda, Kotaro Ogawa, Shuhei Kawabata, Takuro Nii, Tatsusada Okuno, Eri Oguro-Igashira, Makoto Kinoshita, Masatoshi Takagaki, Kenichi Yamamoto, Takashi Kurakawa, Mayu Yagita-Sakamaki, Akiko Hosokawa, Daisuke Motooka, Yuki Matsumoto, Hidetoshi Matsuoka, Maiko Yoshimura, Shiro Ohshima, Shota Nakamura, Hidenori Inohara, Haruhiko Kishima, Hideki Mochizuki, ... Yukinori Okada ⊠ + Show authors

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89 Altmetric Metrics



Using the pangenome for host depletion

nature

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Article Open Access Published: 10 May 2023

A draft human pangenome reference

Wen-Wei Liao, Mobin Asri, Jana Ebler, Daniel Doerr, Marina Haukness, Glenn Hickey, Shuangjia Lu, Julian K. Lucas, Jean Monlong, Haley J. Abel, Silvia Buonaiuto, Xian H. Chang, Haoyu Cheng, Justin Chu, Vincenza Colonna, Jordan M. Eizenga, Xiaowen Feng, Christian Fischer, Robert S. Fulton, Shilpa Garg, Cristian Groza, Andrea Guarracino, William T. Harvey, Simon Heumos, ... Benedict Paten 🖂 + Show authors

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Milestones



How can we use the pangenome to host deplete?





Target Dataset: Characterizing Several Childhood Cancers





Target Dataset

- Therapeutically Applicable Research to Generate Effective Treatments (TARGET) in childhood cancer
- Contains over 13,692 applicable samples that can be translated to low-depth microbial reads
- Various cancer types including:
 - Acute Lymphoblastic Leukemia
 - Acute Myeloid Leukemia
 - Neuroblastoma
 - Osteosarcoma
 - Rhabdoid Tumors
 - High-Risk Wilms Tumors



The Therapeutically Applicable Research to Generate Effective Treatments program is characterizing several childhood cancers.



Childhood Cancer Microbiome Questions

Using Target from CGC

- Can we see differences comparing one cancer type vs. all others using tumor tissue?
- Can we see differences comparing one cancer type vs. all others using 'normal' blood?
- Are the microbes represented in childhood cancers similar to those in corresponding adult cancers?

Using Additional Data Resources

- Can we validate these findings across a larger subset of childhood cancers?
- Can we validate these findings across another dataset with the same cancer types?

Target Dataset Breakdown



Target Dataset WGS: Checking for Contamination







Target Dataset Breakdown



Target Dataset WGS: Blood-Derived Normal



Acute Lymphoblastic Leukemia Phase 2

Kidney – Rhabdoid Tumor

Osteosarcoma

Next steps for Target Data

- Finish analysis of RNA-Sequencing datasets
- Combine analysis of WGS + RNA-Seq as done in Poore et al. (2020)
- Run random forest machine-learning models:
 - Can we see differences comparing one cancer type vs. all others using tumor tissue?
 - Can we see differences comparing one cancer type vs. all others using 'normal' blood?
- Are the microbes represented in childhood cancers similar to those in corresponding adult cancers?

Next step for Cancer Microbiome



G. Sepich-Poore, et al. Science (2021)

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