Topological Network Analysis of Differentially Expressed Genes in Cancer Cells with Acquired Gefitinib Resistance

YOUNG SEOK LEE¹, SUN GOO HWANG², JIN KI KIM¹, TAE HWAN PARK³, YOUNG RAE KIM¹, HO SUNG MYEONG¹, KANG KWON⁴, CHEOL SEONG JANG², YUN HEE NOH¹ and SUNG YOUNG KIM¹

¹Department of Biochemistry, School of Medicine, Konkuk University, Seoul, Republic of Korea;

²Plant Genomics Laboratory, Department of Applied Plant Science,

Kangwon National University, Chuncheon, Republic of Korea;

³Department of Plastic and Reconstructive Surgery, College of Medicine, Yonsei University, Seoul, Republic of Korea;

⁴School of Korean Medicine, Pusan National University, Yangsan, Republic of Korea

Abstract. Background/Aim: Despite great effort to elucidate the process of acquired gefitinib resistance (AGR) in order to develop successful chemotherapy, the precise mechanisms and genetic factors of such resistance have yet to be elucidated. Materials and Methods: We performed a cross-platform metaanalysis of three publically available microarray datasets related to cancer with AGR. For the top 100 differentially expressed genes (DEGs), we clustered functional modules of hub genes in a gene co-expression network and a proteinprotein interaction network. We conducted a weighted correlation network analysis of total DEGs in microarray dataset GSE 34228. The identified DEGs were functionally enriched by Gene Ontology (GO) function and KEGG pathway. Results: We identified a total of 1,033 DEGs (510 up-regulated, 523 down-regulated, and 109 novel genes). Among the top 100 up- or down-regulated DEGs, many genes were found in different types of cancers and tumors. Through integrative analysis of two systemic networks, we selected six hub DEGs (Pre-B-cell leukemia homeobox1, Transient receptor potential cation channel subfamily C member 1, AXL receptor tyrosine kinase, \$100 calcium binding protein A9, S100 calcium binding protein A8, and Nucleotide-binding oligomerization domain containing 2) associated with calcium homeostasis and signaling, apoptosis, transcriptional regulation, or chemoresistance. We confirmed a correlation of expression of these genes in the microarray dataset. Conclusion: Our study may lead to comprehensive insights

Correspondence to: Sung Young Kim, MD, Ph.D., Department of Biochemistry, School of Medicine, Konkuk University, Seoul 143-701, Republic of Korea. Tel: +82 220496060, Fax: +82 220496060, e-mail: palelamp@kku.ac.kr

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into the complex mechanism of AGR and to novel gene expression signatures useful for further clinical studies.

Although chemotherapy is the most common treatment for various cancer types, the development of acquired resistance to anticancer drugs remains a serious problem, leading to a majority of patients who initially responded to anticancer drugs suffering the recurrence or metastasis of their cancer (1-3). Acquired drug resistance (ADR) is known to have a multifactorial etiology, with specific associations that include ethnicity, genetic alterations, epigenetic imbalances, and environmental variations.

Gefitinib, an orally-active synthetic anilinoquinazoline, is a first-generation epidermal growth factor (EGFR)-tyrosine kinase inhibitor that was approved in 2003 by the US Food and Drug Administration for the second-line treatment of advanced non-small cell lung cancer (NSCLC) that harbors EGFR-activating mutations, such as an in-frame deletion in exon 19 or an L858R substitution in exon 21 (4, 5). To antagonize the tyrosine kinase activity of EGFR, gefitinib reversibly binds to the adenosine triphosphate binding pocket of the intracellular tyrosine kinase domain, blocking its autophosphorylation and resulting in the inhibition of subsequent downstream signal transduction (6). For example, inhibition of the downstream signaling pathway (such as phosphatidylinositol-3-kinase (PI3K)-Akt kinase (AKT)mammalian target of rapamycin (mTOR), mitogen-activated protein kinase (MAPK)-extracellular signal-regulated kinase (ERK), and Janus kinase (JAK)-signal transducer and activator of transcription (STAT) pathways prevent cell proliferation, inhibition of programmed cell death (apoptosis), angiogenesis, invasion, or metastasis in many types of epithelial cancers. Despite an early positive clinical response, most patients with EGFR-mutant NSCLC eventually acquire resistance to gefitinib, resulting in the chemotherapeutic failures. Several possible mechanisms for acquired gefitinib resistance (AGR)

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in lung cancer have been proposed, including the following: (i) alterations in the target oncogene, such as alternate expression of tyrosine kinase isoforms and second-site mutations in the tyrosine kinase domain (e.g. a T790, secondary EGFR mutation), altered EGFR trafficking, erb-b2 receptor tyrosine kinase 3 (ERBB3) activation, and expression of the ATPbinding cassette subfamily G member 2 (ABCG2) drug-efflux transporter; (ii) by passing of drug inhibition by oncogene addiction, such as the compensatory activation of downstream signaling pathways and redundant activation of other survival pathways (e.g. mesenchymal-epithelial transition factor amplification, activation of vascular endothelial growth factor, insulin-like growth factor-1, or integrin B1 pathways, hepatocyte growth factor overexpression, and loss of the phosphatase and tensin homolog, and (iii) histological transformation (e.g. epithelial-mesenchymal transformation and small-cell transformation). However, none of these mechanisms has provided a full explanation for AGR, and no definitive genetic factors have been reported for AGR in epithelial cancer, including NSCLC (7-10).

Because cancer research needs insightful observations to determine complex etiologies, researchers introduced high-throughput microarrays to investigate the expression of multiple genes under specific conditions (11, 12). In three published reports of microarray studies on AGR cancer, many differentially expressed genes (DEGs) were suggested as candidate biomarkers of AGR but these individual studies were limited by small sample sizes, low sample quality, and differences in laboratory protocols (13, 14). In order to minimize the uncertainty in these findings, we identified the DEGs that were consistently detected in paired samples from all microarray datasets, using a cross-platform meta-analysis. To organize the results, we also approached available data topologically, performing an integrative analysis of the DEGs at the gene or protein level.

To our knowledge, this is the first report of a cross-platform meta-analysis of multiple gene-expression profiles from microarray datasets associated with AGR.

Materials and Methods

Selection of microarray datasets qualified for meta-analysis. We thoroughly evaluated the suitability of microarray datasets retrieved on Gene Expression Omnibus (GEO) database of National Center for Biotechnology Information (NCBI) (http://www.ncbi.nlm.nih.gov/geo/) and ArrayExpress database of the European Molecular Biology Laboratory–European Bioinformatics Institute (EMBL-EBI) (http://www.ebi.ac.uk/arrayexpress/), according to the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines published in 2009 (15).

Meta-analysis of microarray datasets with different platforms. We performed meta-analysis of multiple gene-expression profiles in microarray datasets obtained using different platforms by means of rank

product algorithm (RankProd package in R, http://www.rproject.org/) implemented in the INMEX online program (http://inmex.ca/INMEX/) (16, 17). Considering AGR cells derived from the same parental cell line, we arbitrarily fixed the sample pair. Before the datasets were analyzed, all probe IDs from each dataset were annotated as EntrezIDs for data consistency, and intensity values for gene expression were log2-transformed and processed by quantile normalization (limma package in R). A list of DEGs (up- or down-regulated) were identified based on p-value (where threshold was p < 0.05) and foldchange (FC) level in a given number of replicates multiplied across different microarray datasets under the nonparametric algorithm, which is statistically rigorous but biologically intuitive.

Gene Ontology (GO) hierarchy and Kyoto Encyclopedia of Genes and Genomes (KEGG) pathway analysis. To discern the implication of DEGs in cancer cell lines with AGR, functional enrichment analysis of GO hierarchy (biological process, molecular function, and cellular component) and KEGG pathways were carried out using the Database for Annotation, Visualization, and Integrated Discovery (DAVID) web-accessible bioinformatics program (http://david.abcc.ncifcrf.gov/) under a significance threshold of p < 0.05.

Gene co-expression network analysis. To construct gene co-expression networks for each of the top 100 up- or down-regulated DEGs, we imported the DEG lists into an extensive database of previously discovered networks and screened for significant gene–gene interactions using the online GeneMANIA program (http://www.genemania.org/) (18, 19). The correlation coefficient between a DEG and additional genes in its network was determined by a GO term (biological process)-based weighting and then was filtered to include only those gene co-expressions above a significance threshold of 0.05.

From the 10 up-regulated or down-regulated genes with the most connected edges in the co-expression networks, the distinct functional modules of the hub DEGs and additional related genes were identified by the fast-greedy HE (G) algorithm of the Community Clusters GLay plugin (http://cytoscape.wodaklab.org/wiki/CommunityStructure Layout) using Cytoscape software (http://www.cytoscape.org/) (20).

Protein–protein interaction (PPI) network analysis. To construct a PPI network for each list of proteins encoded by the top 100 up- or down-regulated DEGs, we imported the lists into the extensive database of already-known networks and screened significant PPIs under the Biological General Repository for Interaction Datasets (BioGRID) (http://thebiogrid.org/). In the top 10 up- or down-regulated protein list with the most connected edges in the PPI network, subnetwork between the hub DEGs-encoding proteins and additional related proteins were analyzed by using the Cytoscape plugin, ClusterONE (http://apps.cytoscape.org/apps/clusterone) (21, 22).

Weighted gene correlation network analysis (WGCNA). To construct a co-expression network of the identified total DEGs in cancer cell lines with AGR, we evaluated Pearson's correlation coefficient values across 1692 microarray probes in the normalized datasets of GSE 34228, which was analyzed using the most samples, by WGCNA (23). During the WGCNA procedure, briefly, Pearson's correlation matrices for all genes were calculated and transformed by raising all values to a power β (soft thresholding as biological networks are small-world and scale-free). Finally, gene co-expression modules were identified from the hierarchical cluster tree by using a dynamic tree cut procedure (24).

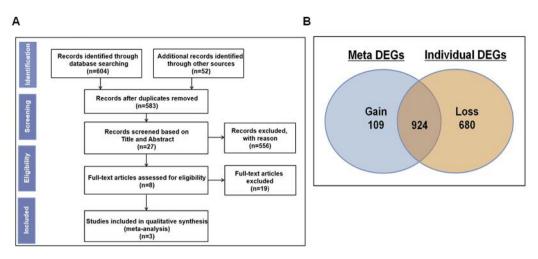


Figure 1. Differential gene expression profiles of this meta-analysis. A: Selection of microarray datasets for meta-analysis of the acquired gefitinib resistant cancer cell lines, according to Prisma 2009 flow diagram. B: Venn diagram showing the number of significant associations between differentially expressed genes (DEGs) identified from the meta-analysis of multiple datasets (Meta-DE) and DEGs identified from the individual analysis of each dataset (individual-DE).

Table I. Characteristics of individual studies retrieved from Gene Expression Omnibus for meta-analysis.

Dataset	San	nple	Drug	Cancer cell	Platform	
-	Gef-S	Gef-R	_			
GSE34228	26	26	Gefitinib	Lung cancer (PC9)	Agilent-014850 Whole Human Genome Microarray 4×44K	
GSE10696	3	3	Gefitinib	Epidermoid carcinoma (A431)	Affymetrix Human Genome U133 Plus 2.0 Array	
GSE38302	1	3	Gefitinib	Lung cancer (PC9)	Agilent-028004 SurePrint G3 Human GE 8×60K	

GSE; Gene expression series, Gef-S; gefitinib-sensitive, Gef-R; gefitinib-resistant

Results

Selection of microarray datasets for meta-analysis related to AGR. Three microarray datasets containing 62 GEO samples were extracted from the GEO database of The NCBI, which met our criteria for meta-analysis (Figure 1A). All three GEO series (GSEs) were microarray expression profiles of only the cancer cell lines that acquire drug resistance by stepwise exposure to increasing doses of gefitinib (Table I). The microarray results of three GSEs were achieved by using two cancer cell lines such as lung cancer (GSE34228 and 38302) and epidermoid carcinoma (GSE10696).

Identification of up- and down-regulated DEGs by meta-analysis. From cross-platform microarray meta-analysis, we identified total 1033 DEGs including 510 up- and 523 down-regulated genes across the three microarray datasets under the significance threshold of p<0.05. While 109 "gained" genes were uniquely identified as DEGs in the meta-analysis, 680

"lost" genes were identified as DEGs in any individual analysis but not in the meta-analysis (Figure 1B). The "gained" genes show relatively weak, but consistent expression profiles across all three datasets, having more reliability to be declared as novel genes. But, the "lost" genes either imply inconsistent changes in expression profiles across different datasets, or large variations by different platforms or experimental errors. The 100 most significantly up- and downregulated DEGs with p<1.0E-5 are listed in Tables II and III, respectively. In the up-regulated DEGs, genes with the largest mean log₂FC were family with sequence similarity 9, member B (FAM9B), followed by patatin-like phospholipase domain containing 4 (PNPLA4) and ankyrin repeat domain 30B pseudogene 2 (ANKRD30BP2). The down-regulated genes with the largest mean log₂FC were by descending order: GPC6, S100A8, and SYNPO2L.

A subset of top 25 dysregulated DEGs across the three microarray datasets was also visualized by heat maps showing differential expression of individual datasets (Figure 2).

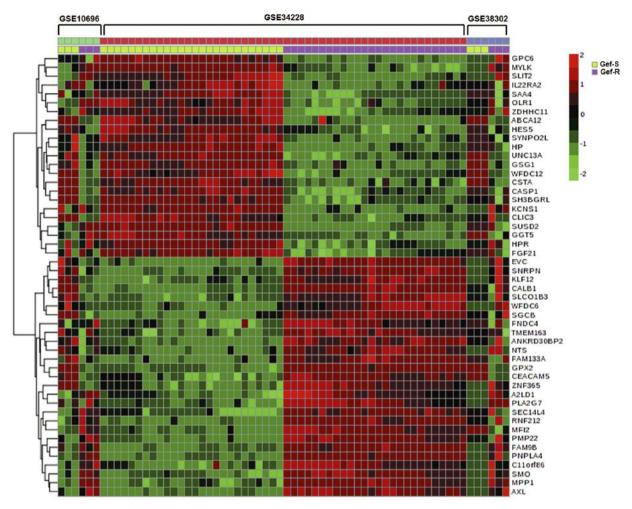


Figure 2. Heat-map representation of expression profiles for the top 25 up- and 25 down-regulated DEGs across three datasets. Clustering of selected genes on the heat-map was performed by hierarchical clustering algorithm using average linkage method and Euclidean distance measure. Gef-S: gefitinib-senstive; Gef-R: gefitinib-resistant.

GO hierarchy and KEGG pathway enrichment analysis of total DEGs. Considering all 1,033 DEGs obtained by the metaanalysis, the most over-represented GO terms in biological processes were enriched in the following descending order: "inflammatory response", "epidermis development", and "response to inorganic substance" (Table IV). The most enriched GO terms in molecular function and cellular component were "calcium ion binding" and "plasma membrane", respectively. The most enriched KEGG pathway terms were as follows (in descending order): "calcium signaling pathway", "phosphatidylinositol signaling system", "cytokine-cytokine receptor interaction", and "pathways in cancer".

Gene co-expression network analysis of DEGs. To interpret the biological meaning of the identified DEGs at the gene level, we constructed a co-expression network for the top 100 up- and

down-regulated DEGs with significant interaction relation composed of 144 nodes/446 edges and 124 nodes/550 edges, respectively. From the co-expression network of up-regulated DEGs, the list of top 10 hub genes was determined in order of number of the interacting edges as follows (in order): peripheral myelin protein 22 (PMP22), echinoderm microtubule associated protein like 1 (EML1), secretogranin II (SCG2), sparc/ osteonectin, cwcv and kazal-like domains proteoglycan 1 (SPOCKI), pre-B-cell leukemia homeobox 1 (PBXI), transient receptor potential cation channel, subfamily C, member 1 (TRPC1), growth arrest-specific 6 (GAS6), phosphodiesterase 2A, cGMP-stimulated (PDE2A), AXL receptor tyrosine kinase (AXL), and prostaglandin I2 synthase (PTGIS). In the network of down-regulated DEGs, the top 10 hub genes with the most connected edges were peptidase inhibitor 3, skin-derived (PI3), S100 calcium binding protein A9 (S100A9), S100A8, chemokine

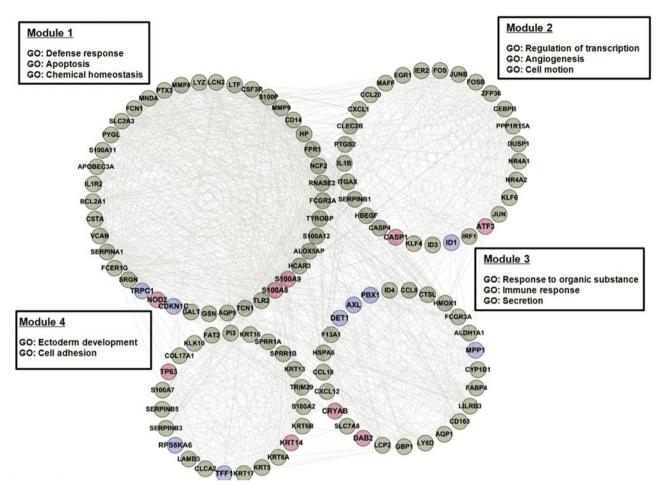


Figure 3. Functional modules of hub genes in gene co-expression network. From gene co-expression networks of the top 100 up- or down-regulated DEGs, four functional modules were clustered by each of the top 10 most interacting hub genes of up- or down-regulated DEGs. The color of node signifies the following: Blue: up-regulated DEGs, Red: down-regulated DEGs, and Light brown: additional genes from GeneMANIA program.

(C-X-C motif) ligand 1 (*CXCL1*), cystatin A (*CSTA*), PDZK1 interacting protein 1 (*PDZK1IP1*), serpin peptidase inhibitor, clade B (ovalbumin), member 2 (*SERPINB2*), nucleotide-binding oligomerization domain containing 2 (*NOD2*), serum amyloid A4, constitutive (*SAA4*), and chitinase 3-like 2 (*CHI3L2*).

The distinct modules of the hub DEGs and their interacting genes were further identified by fast-greedy HE (G) algorithm of GLay Cytoscape plugin (Figure 3). Among the modules, "Module 1", which has the largest size formed by 41 nodes, was significantly enriched by biological process terms such as "defense response", "apoptosis", and "chemical homeostasis" of GO hierarchy.

PPI network analysis of DEGs. In order to interpret the biological meaning of the identified DEGs at the protein level, we constructed a PPI network for the proteins encoded by the top 100 up- or down-regulated DEGs, which were made by

significant interaction including 196 nodes/237 edges and 438 nodes/500 edges respectively.

From the PPI network of proteins encoded by up-regulated DEGs, the list of the top 10 hub proteins was determined in order of number of the interacting edges as follows (in order): ribosomal protein S6 kinase, polypeptide 6 (RPS6KA6), PBX1, inhibitor of DNA binding 1 (ID1), TRPC1, small nuclear ribonucleoprotein polypeptide N (SNRPN), AXL, cyclin-dependent kinase inhibitor 1C (CDKN1C), trefoil factor 1 (TFF1), membrane protein, palmitoylated 1 (MPP1), and detiolated homolog 1 (DET1) (Figure 4).

In the same manner, the top 10 hub proteins encoded by down-regulated DEGs were tumor protein p63 (TP63), crystallin, alpha B (CRYAB), S100A9, activating transcription factor 3 (ATF3), disabled homolog 2 (DAB2), histone cluster 1, H1a (HIST1H1A), S100A8, keratin 14 (KRT14), NOD2, and caspase 1 (CASP1).

Table II. The top 100 most significantly up-regulated genes in the meta-analysis.

Entrez ID	Gene symbol	Log2 FC	Gene name
171483	FAM9B	-3.90125	Family with sequence similarity 9, member B
8228	PNPLA4	-3.39019	Patatin-like phospholipase domain containing 4
149992	ANKRD30BP2	-3.36623	Ankyrin repeat domain 30B pseudogene 2
285498	RNF212	-3.26040	Ring finger protein 212
4354	MPP1	-3.24646	Membrane protein, palmitoylated 1, 55 kDa
87769	A2LD1	-3.04257	Gamma-glutamylamine cyclotransferase
793	CALB1	-2.83337	Calbindin 1, 28kDa
558	AXL	-2.71814	AXL receptor tyrosine kinase
2121	EVC	-2.69040	Ellis van Creveld syndrome
5376	PMP22	-2.68507	Peripheral myelin protein 22
6608	SMO	-2.65570	Smoothened, frizzled class receptor
151827	LRRC34	-2.65214	Leucine rich repeat containing 34
254439	C11orf86	-2.64451	Chromosome 11 open reading frame 86
7941	PLA2G7	-2.57645	Phospholipase A2, group VII (platelet-activating factor acetylhydrolase, plasma)
11278	KLF12	-2.56561	Kruppel-like factor 12
28234	SLCO1B3	-2.56060	Solute carrier organic anion transporter family, member 1B3
84171	LOXL4	-2.52231	Lysyl oxidase-like 4
4241	MFI2	-2.51589	Antigen p97 (melanoma associated) identified by monoclonal antibodies 133.2 and 96
6695	SPOCK1	-2.50976	Sparc/osteonectin, cwcv and kazal-like domains proteoglycan (testican) 1
64838	FNDC4	-2.50655	Fibronectin type III domain containing 4
284904	SEC14L4	-2.49981	SEC14-like 4
6638	SNRPN	-2.45761 -2.45761	Small nuclear ribonucleoprotein polypeptide N
22891	ZNF365	-2.45694	Zinc finger protein 365
94031	HTRA3	-2.43569	HtrA serine peptidase 3
399818	METTL10	-2.41988	Methyltransferase like 10
		-2.39483	Sarcoglycan, beta
6443	SGCB		
89853	FAM125B	-2.37603	Family with sequence similarity 125, member B
140870	WFDC6	-2.34668	WAP four-disulfide core domain 6; serine peptidase inhibitor-like
57732	ZFYVE28	-2.33267	Zinc finger, FYVE domain containing 28
81615	TMEM163	-2.32293	Transmembrane protein 163
5624	PROC	-2.31267	Protein C
148808	MFSD4	-2.28194	Major facilitator superfamily domain containing 4
4922	NTS	-2.25746	Neurotensin
201456	FBXO15	-2.23269	F-Box protein 15
7136	TNNI2	-2.22495	Troponin I type 2
285220	EPHA6	-2.22490	EPH receptor A6
286499	FAM133A	-2.21997	Family with sequence similarity 133, member A
2877	GPX2	-2.20498	Glutathione peroxidase 2
2621	GAS6	-2.20071	Growth arrest-specific 6
116154	PHACTR3	-2.16645	Phosphatase and actin regulator 3
4320	MMP11	-2.14391	Matrix metallopeptidase 11
2568	GABRP	-2.09987	Gamma-aminobutyric acid A receptor
23059	CLUAP1	-2.08400	Clusterin associated protein 1
400655	LOC400655	-2.08052	Hypothetical gene supported by BC013370; BC034583
79923	NANOG	-2.07658	Nanog homeobox pseudogene 8
23671	TMEFF2	-2.06106	Transmembrane protein with EGF-like and two follistatin-like domains 2
8622	PDE8B	-2.05822	Phosphodiesterase 8B
137392	FAM92A1	-2.03892	Family with sequence similarity 92, member A1
646113	FLJ43390	-2.03626	Hypothetical LOC646113
2562	GABRB3	-2.03076	Gamma-aminobutyric acid A receptor, beta 3
171484	FAM9C	-2.00399	Family with sequence similarity 9, member C
80712	ESX1	-2.00289	ESX homeobox 1
80235	PIGZ	-1.99490	Phosphatidylinositol glycan anchor biosynthesis, class Z
5138	PDE2A	-1.97341	Phosphodiesterase 2A, cGMP-stimulated
1048	CEACAM5	-1.96272	Carcinoembryonic antigen-related cell adhesion molecule 5
9863	MAGI2	-1.95602	Membrane associated guanylate kinase
84952	CGNL1	-1.94479	Cingulin-like 1
	J 011 L1	1.01110	Cinguin into i

 ${\bf Table~II.}~Continued$

Table II. Continued

Entrez ID	Gene symbol	Log2 FC	Gene name	
8784	TNFRSF18	-1.92713	Tumor necrosis factor receptor superfamily, member 18	
2054	STX2	-1.91054	Syntaxin 2	
338707	B4GALNT4	-1.90519	Beta-1,4-N-acetyl-galactosaminyl transferase 4	
200407	CREG2	-1.90473	Cellular repressor of E1A-stimulated genes 2	
114879	OSBPL5	-1.90453	Oxysterol binding protein-like 5 Ribosomal protein S6 kinase, 90 kDa, polypeptide 6 RAS guanyl releasing protein 1	
27330	RPS6KA6	-1.89919	Ribosomal protein S6 kinase, 90 kDa, polypeptide 6	
10125	RASGRP1	-1.89060	RAS guanyl releasing protein 1	
27092	CACNG4	-1.88590	Calcium channel, voltage-dependent, gamma subunit 4	
148641	SLC35F3	-1.88486	Solute carrier family 35, member F3	
7857	SCG2	-1.87220	Secretogranin II	
7220	TRPC1	-1.87136	Transient receptor potential cation channel, subfamily C, member 1	
1028	CDKN1C	-1.87109	Cyclin-dependent kinase inhibitor 1C	
138311	FAM69B	-1.86758	Cyclin-dependent kinase inhibitor 1C Family with sequence similarity 69, member B	
55283	MCOLN3	-1.85946	Family with sequence similarity 69, member B Mucolipin 3	
26049	FAM169A	-1.85476	Family with sequence similarity 169, member A	
5141	PDE4A	-1.84987	Phosphodiesterase 4A, cAMP-specific	
59285	CACNG6	-1.84673	Calcium channel, voltage-dependent, gamma subunit 6	
57007	CXCR7	-1.84200	Chemokine (C-X-C motif) receptor 7	
5542	PRB1	-1.81966	Proline-rich protein BstNI subfamily 1	
5740	PTGIS	-1.81753	Prostaglandin I2 (prostacyclin) synthase	
7504	XK	-1.80963	X-linked Kx blood group	
120376	C11orf93	-1.78835	Uncharacterized protein LOC120376	
9966	TNFSF15	-1.78234	Tumor necrosis factor (ligand) superfamily, member 15	
7031	TFF1	-1.78168	Trefoil factor 1	
65009	NDRG4	-1.77721	NDRG family member 4	
58473	PLEKHB1	-1.77451	Pleckstrin homology domain containing	
137209	ZNF572	-1.76607	Zinc finger protein 572	
399693	MGC50722	-1.76511	Zinc finger protein 572 Hypothetical MGC50722	
26960	NBEA	-1.76316	Hypothetical MGC50722 Neurobeachin	
148418	SAMD13	-1.76037	Sterile alpha motif domain containing 13	
2530	FUT8	-1.75395	Fucosyltransferase 8	
4756	NEO1	-1.73991	Neogenin homolog 1	
3397	ID1	-1.73948	Inhibitor of DNA binding 1	
2009	EML1	-1.73573	Echinoderm microtubule associated protein like 1	
57119	SPINLW1	-1.73023	Serine peptidase inhibitor-like, with Kunitz and WAP domains 1	
2039	EPB49	-1.73018	Erythrocyte membrane protein band 4.9	
57547	ZNF624	-1.73016	Zinc finger protein 624	
57493	HEG1	-1.72849	HEG homolog 1	
29785	CYP2S1	-1.72804	Cytochrome P450, family 2, subfamily S, polypeptide 1	
55070	DET1	-1.71702	De-etiolated homolog 1	
5087	PBX1	-1.71510	Pre-B-cell leukemia homeobox 1	
9249	DHRS3	-1.71204	Dehydrogenase/reductase member 3	

 $Log_2FC = log2 \ (class1/class2), FC; \ fold \ change, \ class1; \ gefitinib-sensitive, \ class2; \ gefitinib-resistant.$

The 15 module clusters including the hub proteins were further identified by density of nodes and *p*-value of ClusterONE Cytoscape plugin and six of these clusters shared common genes with the top 10 hub gene lists of the gene coexpression network (Figure 5).

WGCNA of the identified total DEGs in cancer cell lines with AGR. To investigate the functional module eigen (ME) of genes that were highly correlated in microarray dataset GSE34228 with the most samples, we conducted the WGCNA

of total DEGs by R package WGCNA under a scale-free topology of the power adjacency function parameter of 11.

The closely-interacting genes within the network were subdivided into eight distinct MEs using the dynamic hybrid treecutting algorithm and were identified by functional enrichment of GO hierarchy and KEGG pathway (Figure 6). Among them, "MEgrey" was the largest ME of 405 nodes and was significantly enriched by GO terms "regulation of cell proliferation" and KEGG terms "cytokine–cytokine receptor interaction".

Table III. The top 100 most significantly down-regulated genes in the meta-analysis.

Entrez ID	Gene symbol	Log2 FC	Gene name	
10082	GPC6	4.872629	Glypican 6	
5279	S100A8	3.831239	S100 calcium binding protein A8	
9933	SYNPO2L	3.568912	Synaptopodin 2-like	
6154	ABCA12	3.490312	ATP-binding cassette, sub-family A (ABC1), member 12	
475	CSTA	3.397182	Cystatin A (stefin A)	
28488	WFDC12	3.301753	WAP four-disulfide core domain 12	
787	KCNS1	3.250585	Potassium voltage-gated channel, modifier subfamily S, member 1	
451	SH3BGRL	3.218268	SH3 domain binding glutamate-rich protein like	
250	HPR	3.180568	Haptoglobin-related protein	
34	CASP1	3.148989	Caspase 1, apoptosis-related cysteine peptidase	
3445	GSG1	3.123732	Germ cell associated 1	
88585	HES5	3.107186	Hes family bHLH transcription factor 5	
240	HP	3.074056	Haptoglobin	
599	SPRR1B	3.049195	Small proline-rich protein 1B	
266	PI3	3.045197	Peptidase inhibitor 3, skin-derived	
19708	WFDC5	3.008763	WAP four-disulfide core domain 5	
5241	SUSD2	2.984918	Sushi domain containing 2	
1806	CALML5	2.977824	Calmodulin-like 5	
3025	UNC13A			
3023 291		2.862026	Unc-13 homolog A (C. elegans)	
291 589	SAA4	2.749179	Serum amyloid A4, constitutive	
	NCF4	2.69263	Neutrophil cytosolic factor 4	
022	CLIC3	2.67059	Chloride intracellular channel 3	
055	SERPINB2	2.63490	Serpin peptidase inhibitor, clade B (ovalbumin), member 2	
0158	PDZK1IP1	2.60480	PDZK1 interacting protein 1	
576	IL8	2.59001	Interleukin 8	
854	KRT6B	2.58998	Keratin 6B	
16	<i>ALDH1A1</i>	2.58969	Aldehyde dehydrogenase 1 family, member A1	
353	SLIT2	2.57949	Slit homolog 2	
5291	FGF21	2.54931	Fibroblast growth factor 21	
E+08	LOC100130476	2.52279	Similar to hCG2036711	
024	HIST1H1A	2.51167	Histone cluster 1, H1a	
538	MYLK	2.50508	Myosin light chain kinase	
587	GGT5	2.50050	Gamma-glutamyltransferase 5	
7110	HRASLS	2.47448	HRAS-like suppressor	
65	CA6	2.46709	Carbonic anhydrase VI	
17286	CIB3	2.42847	Calcium and integrin binding family member 3	
278	S100A7	2.40512	S100 calcium binding protein A7	
1553	FAM49A	2.39138	Family with sequence similarity 49, member A	
598	IL13RA2	2.37391	Interleukin 13 receptor, alpha 2	
9844	ZDHHC11	2.37258	Zinc finger, DHHC-type containing 11	
853	KRT6A	2.36484	Keratin 6A	
16379	IL22RA2	2.35407	Interleukin 22 receptor, alpha 2	
1254	SLC6A14	2.31839	Solute carrier family 6 (amino acid transporter), member 14	
580	CYP4B1	2.30726	Cytochrome P450, family 4, subfamily B, polypeptide 1	
981	GUCA2B	2.29064	Guanylate cyclase activator 2B	
981 0736				
	SLC44A4	2.28010	Solute carrier family 44, member 4	
117	CHI3L2	2.24191	Chitinase 3-like 2	
110	CRYAB	2.23727	Crystallin, alpha B	
702	SPRR2C	2.22302	Small proline-rich protein 2C (pseudogene)	
1	ABCA4	2.22258	ATP-binding cassette, sub-family A (ABC1), member 4	
124	BBOX1	2.18805	Butyrobetaine (gamma), 2-oxoglutarate dioxygenase 1	
303	COL12A1	2.17887	Collagen, type XII, alpha 1	
973	OLR1	2.14220	Oxidized low density lipoprotein (lectin-like) receptor 1	
4881	PCDH20	2.12045	Protocadherin 20	
702	GJA5	2.07773	Gap junction protein, alpha 5, 40 kDa	
0561	IFI44	2.06929	Interferon-induced protein 44	
280	S100A9	2.05150	S100 calcium binding protein A9	
4550	NECAB2	2.03725	N-Terminal EF-hand calcium binding protein 2	

Table III. Continued

Entrez ID	Gene symbol	Log2 FC	Gene name	
64333	ARHGAP9	2.03643	Rho GTPase activating protein 9	
57115	PGLYRP4	2.03448	Peptidoglycan recognition protein 4	
733	C8G	2.03239	Peptidoglycan recognition protein 4 Complement component 8, gamma polypeptide Keratin 14 Cdc42 GTPase-activating protein Angiotensin I converting enzyme 2 Bone marrow stromal cell antigen 2 Brain abundant, membrane attached signal protein 1 Disabled homolog 2 Chromosome 21 open reading frame 7 Glycerophosphodiester phosphodiesterase domain containing 3 FLJ90680 protein Serpin peptidase inhibitor, clade B, member 3	
3861	KRT14	2.03208	Keratin 14	
57514	ARHGAP31	2.00670	Cdc42 GTPase-activating protein Angiotensin I converting enzyme 2 Bone marrow stromal cell antigen 2 Brain abundant, membrane attached signal protein 1 Disabled homolog 2 Chromosome 21 open reading frame 7 Glycerophosphodiester phosphodiesterase domain containing 3 FLJ90680 protein Serpin peptidase inhibitor, clade B, member 3	
59272	ACE2	2.00009	Angiotensin I converting enzyme 2 Bone marrow stromal cell antigen 2	
684	BST2	1.99884	Bone marrow stromal cell antigen 2	
10409	BASP1	1.99818	Brain abundant, membrane attached signal protein 1	
1601	DAB2	1.99402		
56911	C21orf7	1.98239	e	
79153	GDPD3	1.97767		
400926	FLJ90680	1.96695	FLJ90680 protein	
6317	SERPINB3	1.94860	Serpin peptidase inhibitor, clade B, member 3	
8626	TP63	1.93193	Serpin peptidase inhibitor, clade B, member 3 Tumor protein p63	
51702	PADI3	1.92478	Tumor protein p63 Peptidyl arginine deiminase, type III	
6406	SEMG1	1.90862	Semenogelin I	
64127	NOD2	1.89057	Nucleotide-binding oligomerization domain containing 2	
23569	PADI4	1.88711	Peptidyl arginine deiminase, type IV	
84891	ZSCAN10	1.88550	Zinc finger and SCAN domain containing 10	
4633	MYL2	1.88162	Myosin, light chain 2, regulatory, cardiac, slow	
467	ATF3	1.87826	Activating transcription factor 3	
374454	KRT77	1.87719	Keratin 77	
26471	NUPR1	1.87228	Nuclear protein, transcriptional regulator, 1	
92241	RCSD1	1.87127	RCSD domain containing 1	
387509	GPR153	1.84401	G Protein-coupled receptor 153	
79883	PODNL1	1.83313	Podocan-like 1	
115362	GBP5	1.83305	Podocan-like 1 Guanylate binding protein 5	
6543	SLC8A2	1.83276	Guanylate binding protein 5 Solute carrier family 8, member 2	
725	C4BPB	1.83044	Complement component 4 binding protein, beta	
115572	FAM46B	1.82541	Complement component 4 binding protein, beta Family with sequence similarity 46, member B	
2919	CXCL1	1.81746	Chemokine (C-X-C motif) ligand 1	
360	AQP3	1.81135	Aquaporin 3	
54626	HES2	1.80263	Hairy and enhancer of split 2	
137994	LETM2	1.79409	Leucine zipper-EF-hand containing transmembrane protein 2	
7439	BEST1	1.78287	Bestrophin 1	
8909	ENDOU	1.77794	26 serine protease	
440356	LOC440356	1.77779	Hypothetical LOC440356	
55064	C9orf68	1.77607	Chromosome 9 open reading frame 68	
57451	ODZ2	1.77390	Odz, odd Oz/ten-m homolog 2	
126520	PLK5	1.77288	Polo-like kinase 5 pseudogene	
118611	C10orf90	1.77055	Polo-like kinase 5 pseudogene Chromosome 10 open reading frame 90	
2549	GAB1	1.76527	GRB2-associated binding protein 1	

 $Log_2FC = log2 \ (class1/class2), FC; \ fold \ change, \ class1; \ gefitinib-sensitive, \ class2; \ gefitinib-resistant.$

Discussion

Cancer cells that develop resistance to gefitinib are a major challenge to successful treatment and long-term survival. To date, no clear mechanism for AGR has been demonstrated. A multifarious approach to analyzing the expression patterns of multiple genes in AGR cancer cells could allow us to characterize the overall response of resistant cells and to understand the complex mechanisms underlying gefitinib resistance.

In the gene-expression patterns obtained by the metaanalysis, primary study for p-value and log₂FC of DEGs showed that not few of the top 100 up- or down-regulated DEGs were found in developmental processes of many types of tumor. In the case of top 20 DEGs, in particular, previous studies reported that most of the genes were involved in carcinogenesis of various types of cancer such as of the breast, prostate, stomach, ovary, and lung. In addition, some of these DEGs have been identified in cancer cells with anticancer drug resistance other than AGR, including resistance to cisplatin,

Table IV. The top 15 Gene Ontology hierarchy and Kyoto Encyclopedia of Genes and Genomes pathway enrichment.

ID	Term	Number of genes	<i>p</i> -Value
GO hierarchy			
GO_MF:0005509	Calcium ion binding	91	5.77E-09
GO_BP:0006954	Inflammatory response	35	9.71E-05
GO_BP:0008544	Epidermis development	23	2.59E-04
GO_MF:0008083	Growth factor activity	21	3.19E-04
GO_BP:0010035	Response to inorganic substance	24	4.79E-04
GO_BP:0043067	Regulation of programmed cell death	63	1.76E-03
GO_BP:0001525	Angiogenesis	18	1.95E-03
GO_CC:0005886	Plasma membrane	223	5.28E-03
GO_BP:0007242	Intracellular signaling cascade	87	5.81E-03
GO_BP:0000122	Negative regulation of transcription from RNA polymerase II promoter	25	6.81E-03
GO_BP:0007267	Cell-cell signaling	46	9.95E-03
GO_BP:0051050	Positive regulation of transport	21	1.36E-02
GO_MF:0005543	Phospholipid binding	16	4.80E-02
GO_CC:0005856	Cytoskeleton	81	6.31E-02
GO_CC:0031090	Organelle membrane	48	7.50E-02
KEGG pathway			
Hsa:04020	Calcium signaling pathway	20	2.48E-03
Hsa:04070	Phosphatidylinositol signaling system	11	5.59E-03
Hsa:04060	Cytokine-cytokine receptor interaction	24	1.23E-02
Hsa:05200	Pathways in cancer	28	1.53E-02
Hsa:05219	Bladder cancer	7	2.29E-02
Hsa:04666	Fc gamma R-mediated phagocytosis	10	6.62E-02
Hsa:05223	Non-small cell lung cancer	7	6.66E-02
Hsa:04115	p53 signaling pathway	8	6.96E-02
Hsa:04012	ERBB signaling pathway	9	9.22E-02
Hsa:04630	JAK-STAT signaling pathway	13	1.05E-01
Hsa:04150	mTOR signaling pathway	6	1.13E-01
Hsa:05217	Basal cell carcinoma	6	1.29E-01
Hsa:04010	MAPK signaling pathway	19	1.74E-01
Hsa:04621	NOD-like receptor signaling pathway	6	1.86E-01
Hsa:04370	VEGF signaling pathway	6	1.93E-01

trastuzumab, fluorouracil, taxane, and erlotinib. DEGs implicated include membrane protein, palmitoylated 1 (MPP1), AXL, PMP22, smoothened, frizzled class receptor (SMO), S100A8, Hes family bHLH transcription factor 5 (HES5), ATP-binding cassette, sub-family A, member 12 (ABCA12), haptoglobin (HP), and PI3. Interestingly, we identified 109 "gained" DEGs in this meta-analysis which were not discovered in the prior individual analyses. This large number of "gained" DEGs implies that our approach has a higher likelihood of identifying novel biomarkers for AGR. For the identified DEGs overall, a functional enrichment analysis revealed that a large proportion of these genes were classified as having functions related to cellular processes that oncogenesis, including occur during homeostasis, development, apoptosis, immune response, angiogenesis, and signal transduction. In our gene coexpression network, four distinct modules composed of hub DEGs were classified into typical cellular processes of AGR, including indefinite cell

proliferation and anti-apoptosis (module 1), malfunctioning membrane transport of small molecules (modules 1, 3, and 4), response to chemical compounds (modules 1 and 3), abnormal cell development (modules 2 and 4), angiogenesis (module 2), and dysregulated transcription (module 2). In parallel with the gene co-expression network, 15 module clusters surrounding hub proteins were identified and enriched in the PPI network. By comparing these networks, we recognized six genes in common, including three up-regulated genes (AXL, PBX1, and TRPC1) and three down-regulated genes (S100A9, S100A8, and NOD2). It is notable that TRPC1 and another three downregulated genes were affiliated with "module 1" in the gene co-expression network. The DEGs in "module 1" were enriched with GO (biological process) terms relevant to calcium homeostasis and signaling or apoptosis, as observed in the hub protein clusters from the PPI network. Moreover, "calcium ion binding" and "calcium signaling pathway" ranked first in the top 15 terms of the GO hierarchy and

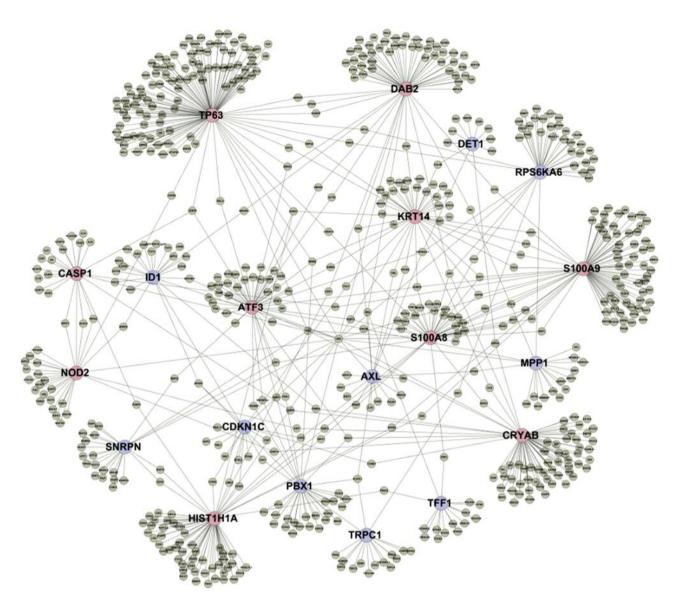


Figure 4. Protein-protein interaction (PPI) network of top 10 lists of up- and down-regulated DEGs based on the number of interactions. We constructed the PPI network of proteins encoded by the top 100 up- or down-regulated DEGs under BioGRID program. From the PPI network, each top 10 lists of up- or down-regulated proteins were identified by the number of connected nodes and analyzed on genome-free scale in Cytoscape software. The color of node signifies proteins that are encoded by the following: Light blue: up-regulated DEGs, Light red: down-regulated DEGs, and Light brown: additional genes in BioGRID.

KEGG pathway enrichment of DEGs overall. Many studies have suggested that dysregulated calcium homeostasis and altered calcium signaling play important roles in antiapoptosis, tumor vascularization, invasion, and metastasis in the carcinogenesis of many tumorigenic cells (25, 26). Joshua *et al.* reported that sustained potentiation of purinergic intercellular calcium signaling was observed following transient exposure to EGF, and that this was not blocked by gefitinib or erlotinib in human glioma cells, suggesting new

therapeutic approaches to gliomas and other tumors (27). The TRP ion channel family has been implicated in the regulation of cancer progression and aggressiveness by modulating calcium influx and downstream signaling in many types of cancers (28). In NSCLC cells, EGF-induced calcium entry through TRPC1 promoted cancer cell proliferation by activating EGFR and escaping G_0/G_1 cell-cycle arrest (29). S100A8 and S100A9 (a multigene family of non-ubiquitous cytoplasmic calcium-binding proteins of the EF-hand type) are

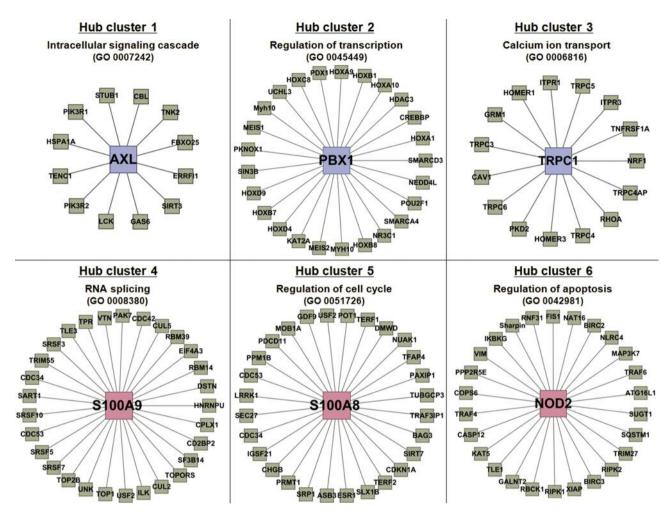


Figure 5. Functional clusters of hub DEG-encoding proteins in PPI network. From PPI networks of proteins encoded by the top 100 up- or down-regulated DEGs, we identified functional module clusters of six hub proteins that were identical with the hub DEGs of the gene co-expression network. The color of node signifies proteins that are encoded by the following: Light blue: up-regulated DEGs, Light red: down-regulated DEGs, and Light brown: additional genes in BioGRID program.

involved in tumor development or progression and have been recently revealed to be associated with the progression of carcinoma cells *via* the Wnt/β-catenin pathway or in MMP2 expression (30-32). NOD2 is known to induce chronic inflammation by mediating anti-apoptosis and autophagy pathways in cancer development (33). AXL and PBX1, both found in "module 2" of the gene co-expression network, have also been reported to be involved in carcinogenesis and tumor development. For example, the AXL receptor tyrosine kinase participates in cell proliferation, invasion and metastasis, and chemoresistance in many types of solid cancers, and causes acquired resistance to EGFR-tyrosine kinase inhibitors by mediating the EMT pathway in NSCLC cells (34). PBX1 forms heterodimeric transcription complexes with other homeodomain-containing nuclear proteins, such as HOX and

HEIS, and regulates expression of important genes in organogenesis, hematopoiesis, and tumorigenesis (35). To determine the correlation of the six candidate DEGs from gene expression profiles of the microarray dataset, we performed a WGCNA of all identified DEGs in GSE34228 and identified eight functional MEs in which genes with highly correlated co-expression were grouped by biological terms of carcinogenesis through functional enrichment. Through our analyses, we confirmed that five DEGs clustered within MEgrey, with NOD2 included in MEred, are contiguous with each other in a hierarchical clustering tree of MEs.

In conclusion, the present study provided comprehensive insights into the complex nature and mechanisms of AGR and novel gene-expression signatures that may be useful for clinical chemotherapy studies.

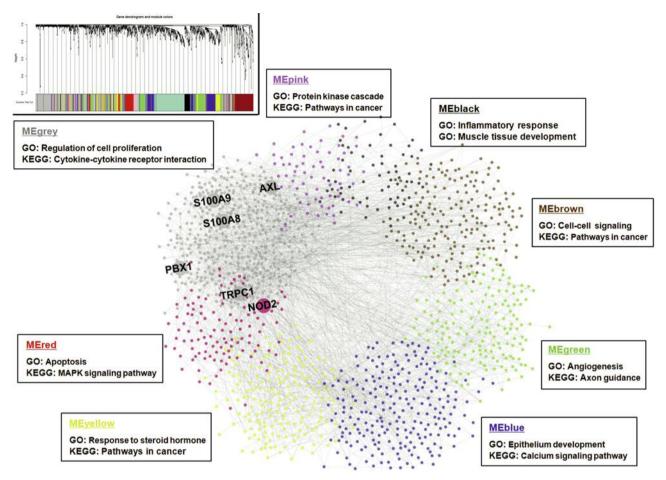


Figure 6. Weighted gene correlation network analysis (WGCNA) of the total DEGs in the microarray dataset "GSE34228". In the GSE34228 dataset with the most samples, we constructed co-expression network of genes that have high correlation among the total 1033 DEGs, by using R package WGCNA. From the network, module detection analysis was performed by dynamic Tree Cut algorithm.

Conflicts of Interest

None.

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