

Construction and Analysis of Tissue-Specific Protein-Protein Interaction Networks in Humans

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Abstract

We have studied the changes in protein-protein interaction network of 38 different tissues of the human body. 123 gene expression samples from these tissues were used to construct human protein-protein interaction network. This network is then pruned using the gene expression samples of each tissue to construct different protein-protein interaction networks corresponding to different studied tissues of the body. This study is helpful for understanding how human protein interactions change in different tissues. In this way, similar tissues of the body and special functions of each tissue, corresponding to their individualized subnetworks, can be identified. We have calculated graph parameters for studying these protein-protein interaction networks and hubs and non-hubs of the studied protein-protein interaction networks are identified. We found a common subnetwork among protein-protein interaction networks of the studied tissues and a tree of tissue similarities has been constructed. We have also found that average correlation coefficient of hubs in human protein-protein interaction networks obeys a normal-like distribution though it is not possible to separate party and date hubs.

Keywords: Protein-Protein Interaction network; Normal human tissue; Human gene expressions; Hubs; Non-hubs.

Introduction

Proteins play essential roles in performing various biological functions in a cell. The most important are the basic cellular processes that they perform within each cell. Studying Protein-Protein Interaction Networks (PINs) on a genome-scale has become possible through advances in high-throughput experimental research. These experiments have generated large amounts of interaction data for several species including *S. cerevisiae* (Uetz *et al.*, 2000; Ito *et al.*, 2001; Ho *et al.*, 2002, Gavin *et al.*, 2006; Krogan *et al.*, 2006), *Escherichia coli* (Butland *et al.*, 2005), *Drosophila melanogaster* (Giot *et al.*, 2003), *Caenorhabditis elegans* (Li *et*

al., 2004), and *Homo sapiens* (Rual *et al.*, 2005; Stelzl *et al.*, 2005). The corresponding PINs are accessible through databases such as IntAct (Hermjakob *et al.*, 2004), DIP (Salwinski *et al.*, 2004), and BioGrid (Bretkretz *et al.*, 2003).

In Humans, DNA microarrays (Schena *et al.*, 1995; Lockhart *et al.*, 1996) have been used to profile gene expression in cancer and other diseases. In cancer, for example, microarray profiling has been applied to classify tumors according to their sites of origin (Su *et al.*, 2001; Ramaswamy *et al.*, 2001; Bloom *et al.*, 2004) to discover previously unrecognized subtypes of cancer (Alizadeh *et al.*, 2000; Bittner *et al.*, 2000; Perou *et al.*, 2000; Bhattacharjee *et al.*, 2001; Garber *et al.*, 2001; Lapointe *et al.*, 2004) to

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predict clinical outcome (van't Veer *et al.*, 2002; Shipp *et al.*, 2002; Leung *et al.*, 2002), and to suggest targets for therapy (Armstrong *et al.*, 2004; Stegmaier *et al.*, 2004). However, the identification of improved markers for diagnosis and molecular targets for therapy will depend on knowledge not only of the expressed genes in the diseased tissues of interest, but also on detailed information about the expression of the corresponding genes across the gamut of normal human tissues. At present our knowledge on differences in gene expression in various human tissues and under different circumstances is incomplete (Su *et al.*, 2002; Saito-Hisaminato *et al.*, 2002; Hsiao *et al.*, 2001; Warrington *et al.*, 2000; Shyamsundar *et al.*, 2005). In recent studies (Zoltan *et al.*, 2008; Bossi and Lehner, 2009; Souiai *et al.*, 2011; Lopes *et al.*, 2011), the common tissue specific subnetworks of different parts of the human body and the housekeeping genes have been identified. These studies are either based on the use of gene expressions or data of PINs from other sources. The clear difference of our work with what they had done is in two parts: First, the method of PIN construction is different. We have proposed a new method; when available gene expression samples from each tissue is not enough to directly construct the PIN. Second, we have tried to find the similar PINs in studied tissues.

In the next sections the proposed methods of PIN construction based on gene expression profiles and methods for calculation of similarities between them are discussed and Analysis of graph related parameters, identification of common subnetworks and PINs similarities are explained.

Materials And Methods

Gene Expression Profiles

123 gene expression samples from 38 different tissues of normal human body were downloaded from Stanford Microarray Database¹. In this database, 44064 human genes were studied (Shyamsundar *et al.*, 2005). These gene expressions are available in the form of a matrix

having 38 rows and 123 columns. The columns represent samples and the rows represent the gene profiles. The gene expression profiles are normalized in a z-score fashion such that the average expression ratio of one profile is 0 and the standard deviation is 1. In the case where gene expressions are not provided, the average of the gene expressions in the other samples are used instead.

It should be mentioned that they have named the Buffycoat as a tissue although it is not really a tissue of the body. We used those data in our experiments as gene expressions can be obtained from that blood layer.

Protein-Protein Interaction Network Construction Method

Using the gene expression data, we constructed a sparse co-expression network using the k mutual nearest neighbor criterion (Agrawal, 2002). In this method, a list of k nearest neighbor profiles is produced for every gene expression profile. The nearest neighbor of one expression profile is defined as the most similar profile by the Euclidean similarity measure;

$$d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (1),$$

Where x_i , and y_i are the corresponding x and y values in an n dimensional space and n is the number of samples. In this way, a list of k nearest neighbors of each gene (protein) is constructed. Two nodes are connected if they are on each others' list. This way, a gene co-expression network is constructed. The optimal k is 15 (Agrawal and Domany, 2003).

Pruning Human Protein-Protein Interaction Network In Different Tissues Using Different Cut-off Methods

Identifying active and inactive genes of each tissue needs a criterion. A gene is active if its gene expression value is above a specified threshold otherwise it is inactive. A good threshold for this purpose should be the one that is extracted from

1. http://smd.stanford.edu/cgi-bin/publication/viewPublication.pl?pub_no=426

the data itself. We used the statistics of the data for this purpose. We calculated average, average minus variance, average minus $0.5 \times$ variance, average plus variance, average plus $1.5 \times$ variance, and median thresholds. In this way, if the gene expression of a protein in a tissue of the body is above the calculated threshold, this protein is active, otherwise it is inactive and all of its interactions with the rest of the network are omitted. In this way, 38 PINs corresponding to 38 studied tissues are obtained by pruning the original constructed PIN.

Average Cut-off Method

In finding the cut-off values using average method, we calculated average gene expressions of each gene in 123 available samples. We used these calculated averages as cut-off values. In each tissue of the body, we compared the expression profile of each gene with its average within available samples. If the average gene expression value in that tissue is above the average of its values in the whole samples, gene is active otherwise it is inactive.

Average Minus Variance Cut-off Method

In finding the cut-off values using average minus variance method, we calculated average and variance of gene expression profiles for each gene in 123 available samples. For each tissue, we compared the expression profile of each gene with its average minus variance value of the samples. If the gene expression value in that tissue is above that threshold, gene is active otherwise it is inactive.

Cut-off values in Average plus $0.5 \times$ Variance, Average plus Variance, and Average plus $1.5 \times$ variance are calculated in a similar manner.

Median Cut-off Method

In finding the cut-off values using median method, we calculated median of gene expression profiles for each gene using available samples. We used these calculated values as cut-off points. In each tissue of the body, we compared the expression profile of each gene with its median from samples. If the gene expression is above the median of its values in the whole samples, gene

is active.

Graph Related Parameters

The formal representation of PINs as undirected graphs makes it possible to utilize a variety of well-established graph measures. We have computed 12 individual graph measures that reflect the following graph properties: size, distribution, relevance, density, and modularity. The following parameters are calculated: closeness, graph diameter, index of aggregation, entropy of distribution of edges, connectivity, number of edges divided by the number of vertices, entropy, graph centrality, sum of the Wiener number, modified vertex distance number, and Eigen values. More information on these twelve parameters can be found in (Platzer *et al.*, 2007).

Dynamic Behavior of Interactions And Hubs In Different Human Tissues

We calculated number of hubs and interactions of the obtained PINs to see how they change among different tissues. Number of interactions is the summation of all interactions inside the whole PIN. If protein A has interaction with protein B, Protein B also interacts with protein A. Thus, numbers of actual interactions were calculated as summation of all vertex degrees.

Hub proteins are defined as the proteins with most interactions within the PINs. Usually proteins with more than eight interactions are called hubs (Komurov and White, 2007). We used this definition to separate hubs from non-hubs. Hubs are further divided into low connectivity and high connectivity groups. Hubs with up to ten interactions grouped in low connectivity hubs and the ones with more than ten interactions are called high connectivity hubs.

Identifying Party Hubs And Date Hubs of Human Protein-Protein Interaction Networks

In comparison to date hubs, party hubs are defined as proteins that show high average Pearson Correlation Coefficients (PCC) with their interacting partners as defined by Han *et al.* (Han *et al.*, 2004). The point between two peaks in the bimodal distribution of the hubs and their

partners are selected as the threshold for separating party hubs from date hubs (Hen *et al.*, 2004).

In another definition, if gene expression values of a protein vary significantly in different situations or conditions, this protein is assumed dynamic otherwise static (Komurov and White, 2007).

We calculated the average PCC of each hub and its interacting partners using available samples and then estimated the distribution of average PCCs for hubs. We have also calculated variance of gene expressions of each protein in the available samples of these 38 tissues. This way we have labeled proteins as static or dynamic.

We have used two cut-off methods for identifying static and dynamic proteins of humans. Here the methods are explained in more details.

Cut-off Method Based on Histogram of The Data

Histogram of the gene-expression variances/variances divided by averages for all the genes in different samples is plotted. The threshold is placed where the plotted figure is almost smooth. Proteins are labeled dynamic if their gene expressions are above the obtained threshold otherwise they are called static.

In these methods, one cut-off value for all the genes is computed.

Similarity of Pins of Human Tissues

To identify the most similar tissues of the human body based on their functions or PINs, we calculated pairwise similarity of PINs using common edges in the networks. This means that for each pair of PINs numbers of common edges/common functions are calculated. This similarity measure is then normalized and used for clustering the PINs and constructing a hierarchical tree of human similar tissues. We used Matlab hierarchical clustering tool¹ for this purpose.

Results

We studied the changes of human Protein Interaction Networks (PINs) within normal tissues. We constructed a general human PIN

using expression profiles of human genes in 123 samples from 38 different tissues of the body. The constructed human PIN contains 44064 genes and 25245 edges among these nodes.

We have studied the differences of PINs in different tissues of the body. For this purpose, the constructed human PIN was pruned using the gene expression samples from each tissue to obtain a tissue specific PIN. To prune the original PIN for each tissue where more than one sample of that tissue gene expressions are available, the average of the gene expression from that tissue was used and the network is pruned according to the procedure explained in materials and methods. This way 38 different PINs corresponding to 38 different tissues of the body are obtained. Name of these tissues and available samples from each tissue to prune the original network is specified in table 1. The number of active genes in each tissue based on three applied cut-off methods is shown in table 2. As the obtained results show median, and average methods omit a lot of genes from each tissue. We wanted to study the dynamics where most of the genes are active therefore method of average minus variance was selected as the cut-off method to prune the original PIN.

For the first step in analyzing the differences of tissues PINs, number of edges and hubs of both the original network and the 38 tissue-specific networks were calculated. These results are shown in table 3 and 4. As it can be seen from the results, lymph node has the maximum number of edge (23752) and seminal vesicle has the maximum number of hubs (1041) among the studied tissues. The minimum number of edges (17368) belongs to occipital cortex of brain and the minimum number of hubs (485) is in colon tissue.

Graph related parameters including closeness, graph diameter, index of aggregation, entropy of edge distribution, connectivity, number of edges divided by the number of vertices, entropy, graph centrality, sum of the Wiener number, modified vertex distance number, and Eigen values were calculated as introduced by Plazer (Platzer *et al.*, 2007). The results are shown in Table 5. It can be seen that most of the measured graph related

1. www.mathworks.com/help/toolbox/stats/linkage.html

Table 1. Gene Expression Samples from each tissue of the Normal Human body.

Number	Tissue Name	Number of Samples	Sample Names
1	Brain, frontal cortex	3	GSM39887,GSM39907,GSM39946
2	Brain, occipital cortex	3	GSM39888,GSM39908,GSM39937
3	Uterus	4	GSM39889,GSM39902,GSM39952,GSM39988
4	Colon	3	GSM39890,GSM39943,GSM39945
5	Salivary gland	4	GSM39891,GSM39900,GSM39901,GSM39920
6	Ovary	5	GSM39892,GSM39897,GSM39917,GSM39977, GSM39981
7	Uterine corpus	1	GSM39893
8	Vagina	1	GSM39894
9	Bladder	2	GSM39895,GSM39918
10	Adrenal	4	GSM39896,GSM39906, GSM39961,GSM39986
11	Thymus	2	GSM39898,GSM39942
12	Stomach	4	GSM39899,GSM39922,GSM39970,GSM39974
13	Testes	3	GSM39903,GSM39958,GSM39973
14	Diaphragm	1	GSM39904
15	Brain, temporal cortex	2	GSM39905,GSM39935
16	Lung	4	GSM39909,GSM39912,GSM39921,GSM39969
17	Prostate	6	GSM39910,GSM39911,GSM39913,GSM39916, GSM39982,GSM40004
18	Small bowel	3	GSM39914,GSM39936,GSM39959
19	Kidney	5	GSM39915,GSM39924,GSM39926,GSM39956, GSM39983
20	Cervix	3	GSM39919,GSM39923,GSM39949
21	Parathyroid	3	GSM39925,GSM39940,GSM39953
22	Seminal vesicle	7	GSM39927,GSM39928,GSM39932
23	Tonsil		GSM39929,GSM39931,GSM39944,GSM39951
24	Lymph node	5	GSM39930,GSM39933,GSM39941,GSM39950, GSM39954
25	Spleen	3	GSM39934,GSM39963,GSM39971
26	Liver	5	GSM39947,GSM39948,GSM39968,GSM39976, GSM39984
27	Placenta	1	GSM39955
28	Pancreas	2	GSM39957,GSM39990
29	Epididymus	1	GSM39960
30	Fallopian tube	4	GSM39962,GSM39964,GSM39991,GSM40000
31	Breast	1	GSM39965
32	Esophagus	3	GSM39966,GSM39978, GSM39979
33	Muscle	2	GSM39967,GSM39989
34	Thyroid	6	GSM39972,GSM39985,GSM39995,GSM39996, GSM39997,GSM39998
35	Heart	6	GSM39975,GSM39980,GSM39992,GSM39994, GSM39999,GSM40001
36	Pericardium	1	GSM39987
37	Gallbladder	1	GSM39993
38	Buffycoat	2	GSM39938,GSM39939

Table 2. Number of proteins in human tissues based on different cut-off methods.

Cut-off Method/ Human Tissue	Avg.-Var.	Median	Avg.	Correlation Based
Brain, frontal cortex	38979	17898	17913	18111
Brain, occipital cortex	37436	19849	19741	19976
Uterus	41608	21710	21531	22174
Colon	39853	17680	18122	17583
Salivary gland	39581	24066	23548	23329
Ovary	41453	24755	24236	24033
Uterine corpus	40190	34507	29644	29337
Vagina	39067	33842	31688	29806
Bladder	39264	26707	25772	25934
Adrenal	40580	24100	24059	23681
Thymus	39607	18036	17953	18877
Stomach	40992	20295	20244	20452
Testes	39023	20689	20482	20871
Diaphragm	37757	22984	22732	22756
Brain, temporal cortex	39628	17340	16475	17556
Lung	40002	20479	20281	20799
Prostate	41723	22654	22429	22347
Small bowel	40461	16634	17342	18162
Kidney	41531	20080	19828	20282
Cervix	40839	29822	30104	29635
Parathyroid	40638	20724	20473	21801
Seminal vesicle	40337	30058	26940	27264
Tonsil	39418	22861	22032	22312
Lymph node	41354	19033	19375	20248
Spleen	37658	21641	21640	21634
Liver	38871	21526	21367	21571
Placenta	40708	15231	15864	18513
Pancreas	39572	20227	20604	19998
Epididymus	39894	14657	15972	17844
Fallopian tube	37490	22003	21867	22032
Breast	36563	20010	19728	20701
Esophagus	37181	22216	21960	21902
Muscle	36257	23110	23128	22651
Thyroid	37760	19878	19539	20165
Heart	39598	19549	19647	19667
Pericardium	38951	31793	28930	27473
Gallbladder	37697	13598	13813	14861
Buffycoat	40895	21317	20182	21539

Table 3. Number of Edges and Hubs in the Original Human PPI.

Cut-off Method/ Tissue	Edges Number	Hubs Number	8<=Hubs<=10	Hubs<=10
Human	25245	1106	699	407

Table 4. Number of Edges and Hubs in Tissue Networks with Average – Variance cut-off method.

Cut-off Method/ Human Tissue	Edges Number	Hubs Number	8<=Hubs<=10	Hubs<=10
Brain, frontal cortex	19330	607	436	171
Brain, occipital cortex	17368	499	377	122
Uterus	22191	817	598	219
Colon	18407	485	383	102
Salivary gland	22255	1015	639	376
Ovary	23210	980	655	325
Uterine corpus	22962	1020	636	384
Vagina	20962	896	549	347
Bladder	21819	953	624	329
Adrenal	22709	958	643	315
Thymus	21228	810	555	255
Stomach	20837	724	500	224
Testes	19709	684	512	172
Diaphragm	20511	872	569	303
Brain, temporal cortex	20961	798	551	247
Lung	19920	659	488	171
Prostate	22946	955	631	324
Small bowel	22540	971	610	361
Kidney	21197	684	497	187
Cervix	21627	870	580	290
Parathyroid	22781	978	628	350
Seminal vesicle	23293	1041	655	386
Tonsil	21755	906	594	312
Lymph node	23752	1034	662	372
Spleen	18342	606	464	142
Liver	19756	756	539	217
Placenta	22591	971	611	360
Pancreas	18492	532	370	162
Epididymus	22124	951	604	347
Fallopian tube	17697	581	428	153
Breast	17999	663	501	162
Esophagus	18743	725	525	200
Muscle	17977	626	461	165
Thyroid	17945	567	428	139
Heart	20605	781	541	240
Pericardium	20298	798	542	256
Gallbladder	18530	599	440	159
Buffycoat	22099	934	574	360

Table 5. Graph Related Parameters in Different Tissues of the Normal Human Body.

Module Name	TotalCC	VarCC	GD	IOA	Hdist	Conn.*	NeNv	Hent	meanGC	varGC	meanW	varW	mVD
Human PIN	286.8164	0.1762	0.0156	1	NaN	0.0027	1.0299	1.2393e+3	0.5335	0.1302	27.2731	3.2856e+3	2.3789e+3
Brain, frontal	3.8685e+3	0.1564	0.0034	1	1.5833	1.4832e-4	1.1725	1.3542e+5	0.3091	0.1620	4.9440e+4	1.7430e+9	5.8259e+5
Brain, occipital	3.8540e+3	0.1616	0.0043	1	1.5242	1.5134e-4	1.1199	1.0973e+5	0.3273	0.1675	4.2958e+4	1.5011e+9	4.5566e+5
Uterus	4.0127e+3	0.1506	0.0029	1	1.6450	1.4171e-4	1.2313	1.7069e+5	0.2931	0.1576	5.8034e+4	2.1699e+9	7.5982e+5
Colon	4.0536e+3	0.1603	0.0037	1	1.5157	1.3989e-4	1.1100	1.1594e+5	0.3216	0.1662	4.9096e+4	1.8175e+9	5.0640e+5
Salivary gland	3.7898e+3	0.1510	0.0030	1	1.7101	1.5971e-4	1.3091	1.8180e+5	0.2942	0.1577	5.3947e+4	1.8626e+9	7.3209e+5
Ovary	3.9403e+3	0.1491	0.0031	1	1.6891	1.4641e-4	1.2810	1.8755e+5	0.2856	0.1560	5.9679e+4	2.1662e+9	8.4466e+5
Uterine corpus	3.7604e+3	0.1468	0.0030	1	1.7102	1.5396e-4	1.3063	1.8851e+5	0.2832	0.1537	6.0190e+4	2.1489e+9	7.8929e+5
Vagina	3.8487e+3	0.1549	0.0036	1	1.6622	1.5818e-4	1.2630	1.6285e+5	0.3034	0.1619	5.4395e+4	2.0430e+9	6.0441e+5
Bladder	3.8247e+3	0.1524	0.0034	1	1.6961	1.5856e-4	1.2911	1.7540e+5	0.2962	0.1600	5.4145e+4	1.9332e+9	7.1519e+5
Adrenal	3.8453e+3	0.1483	0.0044	1	1.6851	1.4866e-4	1.2763	1.8206e+5	0.2799	0.1579	6.1214e+4	2.4539e+9	8.0592e+5
Thymus	3.8625e+3	0.1532	0.0034	1	1.6514	1.5085e-4	1.2415	1.6305e+5	0.2969	0.1592	5.2729e+4	1.8524e+9	7.0608e+5
Stomach	4.0141e+3	0.1548	0.0046	1	1.6068	1.4285e-4	1.1965	1.5231e+5	0.2981	0.1638	5.8086e+4	2.5094e+9	6.4933e+5
Testes	3.8188e+3	0.1551	0.0042	1	1.6042	1.5031e-4	1.1923	1.4208e+5	0.3029	0.1623	4.9833e+4	1.8523e+9	5.8375e+5
Diaphragm	3.6622e+3	0.1536	0.0032	1	1.6780	1.6431e-4	1.2728	1.6053e+5	0.2997	0.1597	5.0616e+4	1.6715e+9	6.4933e+5
Brain, temporal	3.8822e+3	0.1535	0.0038	1	1.6411	1.5030e-4	1.2311	1.5900e+5	0.2988	0.1600	5.1768e+4	1.8775e+9	6.7556e+5
Lung	3.9698e+3	0.1561	0.0032	1	1.5903	1.4546e-4	1.1794	1.4169e+5	0.3117	0.1616	4.8307e+4	1.7279e+9	5.9418e+5
Prostate	3.9554e+3	0.1493	0.0031	1	1.6814	1.4659e-4	1.2742	1.8385e+5	0.2907	0.1562	5.6464e+4	2.0842e+9	7.9575e+5
Small bowel	3.8902e+3	0.1513	0.0031	1	1.6888	1.5174e-4	1.2845	1.8126e+5	0.2901	0.1583	5.9482e+4	2.1667e+9	7.4512e+5
Kidney	4.0440e+3	0.1527	0.0033	1	1.6045	1.3913e-4	1.1914	1.5493e+5	0.2995	0.1598	5.7373e+4	2.2005e+9	6.7249e+5
Cervix	3.9885e+3	0.1533	0.0027	1	1.6417	1.4651e-4	1.2354	1.6539e+5	0.3028	0.1583	5.1045e+4	1.7892e+9	7.3944e+5
Parathyroid	3.8486e+3	0.1487	0.0030	1	1.6885	1.4965e-4	1.2827	1.8343e+5	0.2855	0.1550	5.9782e+4	2.1780e+9	7.8357e+5
Seminal vesicle	3.8170e+3	0.1494	0.0031	1	1.7170	1.5342e-4	1.3138	1.9279e+5	0.2805	0.1562	6.1506e+4	2.1442e+9	8.5533e+5
Tonsil	3.7481e+3	0.1504	0.0045	1	1.6802	1.5481e-4	1.2738	1.7240e+5	0.2836	0.1595	5.9921e+4	2.3588e+9	7.1146e+5
Lymph node	3.9103e+3	0.1485	0.0031	1	1.7073	1.4776e-4	1.3024	1.9573e+5	0.2798	0.1556	6.2454e+4	2.2477e+9	8.9473e+5
Spleen	3.8512e+3	0.1613	0.0044	1	1.5685	1.5363e-4	1.1610	1.2506e+5	0.3198	0.1662	4.4513e+4	1.6417e+9	4.7469e+5
Liver	3.8739e+3	0.1577	0.0038	1	1.6105	1.5293e-4	1.2041	1.4389e+5	0.3101	0.1633	4.8637e+4	1.7817e+9	5.6783e+5
Placenta	3.9080e+3	0.1510	0.0028	1	1.6854	1.5074e-4	1.2818	1.8128e+5	0.2918	0.1571	5.8001e+4	2.0682e+9	7.6277e+5
Pancreas	3.9871e+3	0.1604	0.0042	1	1.5379	1.4512e-4	1.1332	1.2104e+5	0.3195	0.1671	5.0935e+4	2.0439e+9	4.6567e+5
Epididymus	3.8430e+3	0.1520	0.0035	1	1.6867	1.5446e-4	1.2835	1.7709e+5	0.2915	0.1585	5.6846e+4	2.0121e+9	7.2657e+5
Fallopian tube	3.7914e+3	0.1615	0.0059	1	1.5596	1.5763e-4	1.1542	1.1845e+5	0.3219	0.1697	4.4895e+4	1.8169e+9	4.7934e+5
Breast	3.6460e+3	0.1605	0.0049	1	1.5988	1.6538e-4	1.1928	1.2703e+5	0.3144	0.1673	4.6333e+4	1.7335e+9	4.5691e+5
Esophagus	3.7528e+3	0.1598	0.0039	1	1.6126	1.6229e-4	1.2069	1.3542e+5	0.3179	0.1653	4.3875e+4	1.5495e+9	4.9810e+5
Muscle	3.6026e+3	0.1571	0.0053	1	1.5938	1.6371e-4	1.1860	1.2592e+5	0.3112	0.1663	4.7467e+4	1.7931e+9	4.9476e+5
Thyroid	3.7355e+3	0.1575	0.0043	1	1.5548	1.5346e-4	1.1472	1.1943e+5	0.3145	0.1652	4.6476e+4	1.6922e+9	5.1296e+5
Heart	3.8338e+3	0.1529	0.0033	1	1.6309	1.5041e-4	1.2206	1.5424e+5	0.2988	0.1602	5.3928e+4	1.9642e+9	6.5225e+5
Pericardium	3.7379e+3	0.1526	0.0049	1	1.6388	1.5516e-4	1.2301	1.5274e+5	0.2953	0.1616	5.4636e+4	2.1745e+9	5.9670e+5
Gallbladder	3.7408e+3	0.1573	0.0043	1	1.5802	1.5421e-4	1.1694	1.2823e+5	0.3118	0.1629	4.4047e+4	1.5710e+9	5.0181e+5
Buffycoat	3.9433e+3	0.1529	0.0033	1	1.6673	1.5017e-4	1.2648	1.7397e+5	0.2953	0.1594	5.8527e+4	2.2395e+9	6.9140e+5

* Connectivity

parameters are in the same range for different tissues. That means the global properties of these networks do not change significantly from one tissue to the others. This result shows that topology of PINs in different tissues of the body are similar. Therefore, the differences among cells are because of the constructing elements of the PINs not their topology.

As the next step in analyzing the differences between PINs of tissues, intersection of all PINs were calculated. A network with 831 edges among 792 genes is the common network/modules among these 38 PINs. This network can be seen in Figure 1. It is the part that exists in all the tissues so it must show a general function that all the tissues handle. They are a small fraction of the whole interactions (3.1%). If one needs to study a tissue specifically, this general part can be omitted for simplicity and it can be assumed that the specific functions of tissues are not in the common part.

As the last step in identifying the similarities and differences among different tissues, a hierarchical tree based on these network similarities is constructed. It can be observed that some of the studied network tissues are more similar. That means these PINs have some similar functions. This finding can be used in the case where some simulations or artificial tissues are designed or in the study of similar and dissimilar tissues. This tree is shown in Figure 2. The numbers in the leaves of the tree are corresponding to different tissue names as labeled in table 1. We found ovary, tonsil and epididymus in the same cluster. Salivary gland and bladder are most similar in the interactions. Also it has been revealed that different parts of the brain including frontal, occipital, and temporal cortex are also similar in the interactions and functions.

For identifying party hubs and date hubs of the human PINs, we calculated the average PCC of each hub and its interacting partners using available samples and then we estimate the distribution of average PCCs for hubs. The estimated distribution is shown in Figure 3. This distribution is normal-like distribution though it is not possible to separate party hubs and date hubs using this data and its associated distribution. We have also calculated variance of gene expressions of each protein in the available samples of these 38 tissues. We have calculated

the cut-off points for separating static and dynamic proteins using two different methods of histogram of variance and histogram of variance divided by average of the gene expression values. This way we have labeled proteins as static or dynamic according to their variances. This data is provided in supplementary file I. As the result shows, using the histogram of variance, 123 dynamic proteins are identified whereas histogram of variance divided by average separates 138 dynamic proteins. Choice of method will depend on the number of dynamic genes that is needed to study.

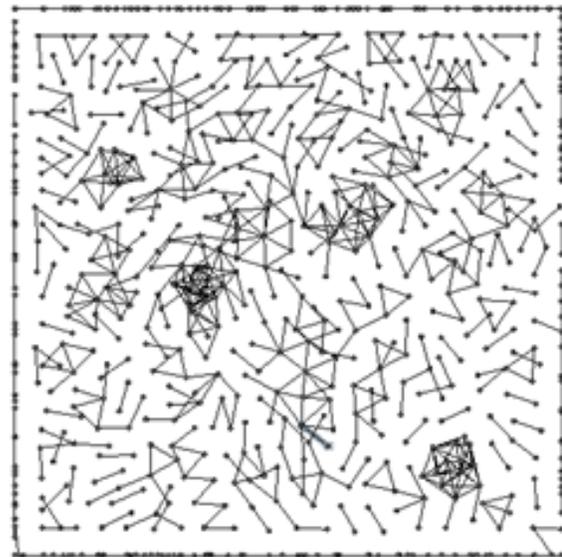


Figure 1. The common network among 38 body tissues.

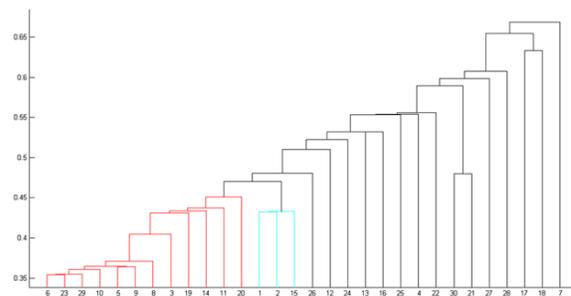


Figure 2. Hierarchical tree of tissue similarities.

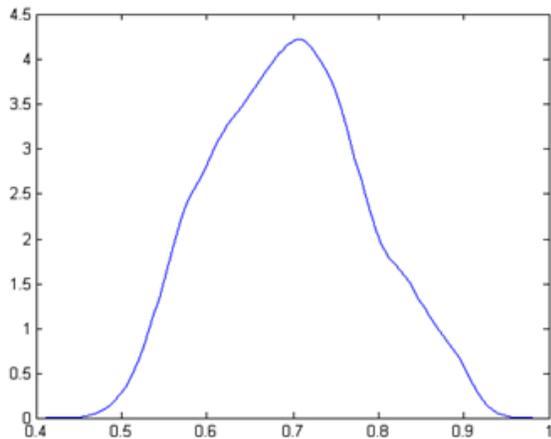


Figure 3. Distribution of average PCC of hubs in human proteins interaction network.

Discussion And Conclusions

In this paper, we studied the human proteins in different tissues of the body. We were looking to see how functions may change from one tissue to the other. In this study, it has been shown that some proteins are not expressed in some of the tissues while they are active in the others. This observation shows that different tissues have different functionalities while they use the same set of genes. That is because different genes are activated in different tissues of the body and their interaction patterns will change from one tissue to the other. A common subnetwork is found in the studied tissues which is responsible for housekeeping and transferring. We have constructed a tree based on similarities of these tissue specific PINs. Some of the tissues are most similar according to this study that means they must have similar functionalities such as three different parts of brain.

We have also studied the changes in the number of hubs and edges of the PINs of the human tissues. We have calculated some of the graph related features of the PINs to see how they are changing from one tissue to the other. We have also estimated the distribution of average PCC among hubs. This distribution does not show a bimodal distribution to allow separating party hubs from date hubs. This result confirms the other studies in which bimodal distributions for separating party and date hubs have not been found (Agarwal *et al.*, 2010).

Finally it should be mentioned that we have used the dataset provided by Shyamsunder *et al.* (Shyamsundar *et al.*, 2005). It has been reported that the choice of dataset can influence the tissue-specific protein-protein interaction studies (Lopes *et al.*, 2011), so we cannot generalize our results before testing them on other datasets as well.

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