Systems biology

Phenotypic categorization of genetic skin diseases reveals new relations between phenotypes, genes and pathways

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ABSTRACT

Motivation: Systematic analysis of connection between proteins, their cellular function and phenotypic manifestations in disease is a central problem of biological and clinical research. The solution to this problem requires the development of new approaches to link the rapidly growing dataset of gene-disease associations with the many complex and overlapping phenotypes of human disease.

Results: We analyze genetic skin disorders and suggest a manually designed set of elementary phenotypes whose combinations define diseases as points in a multidimensional space, providing a basis for phenotypic disease clustering. Placing the known gene-disease associations in the context of this space reveals new patterns that suggest previously unknown functional links between proteins, signaling pathways and disease phenotypes. For example, analysis of telangiectasias (spider vein diseases) reveals a previously unrecognized interplay between the TGF-β signaling pathway and pentos phosphate pathway. This interaction may mediate glucose-dependent regulation of TGF-β signaling, providing a clue to the known association between angiopathies and diabetes and implying new gene candidates for mutational analysis and drug targeting.

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1 INTRODUCTION

Rigorous quantitative analysis of disease phenotypes is a key problem on our way to understanding systemic effects of human gene mutations. Such understanding would enable statistical prediction of clinical manifestations for genome abnormalities, inference of causative genes from complex disease phenotypes, as well as deeper insights into molecular mechanisms of pathophysiology. This tremendous task requires the development of new approaches to link the rapidly growing dataset of gene–disease associations with the many complex and overlapping phenotypes of human disease.

Previously reported approaches to this problem ranged from considering diseases as individual entities connected through shared causative genes (Goh et al., 2007) or co-occurrence in the same patient (Rzhetsky et al., 2007), to more detailed classifications involving the comparison of disease phenotypes, usually based on ontologies of phenotypic terms derived from natural-language phenotype descriptions through automated or semi-automated text analysis (Robinson et al., 2008; van Driel et al., 2006). These analyses may include additional high-throughput data on protein associations (Lage et al., 2007; Wu et al., 2008), improving prediction of new connections between diseases and proteins involved. Here we suggest a different approach to quantitative gene-phenotype analysis. By focusing on the set of genetic skin disorders, we are able to manually analyze the corresponding descriptions of phenotypic manifestations and design a set of elementary phenotypic features whose combinations define any given disease as a point in a multidimensional space. Placing the known gene–disease associations in the context of this space reveals new patterns that suggest previously unknown functional links between disease phenotypes, proteins and signaling pathways. In particular, analysis of telangiectasias (spider vein diseases), reveals a previously unrecognized interplay between the TGF-β signaling cascade and pentos phosphate pathway (PPP), which may mediate glucose-dependent regulation of TGF-β signaling in diabetes.

2 METHODS

The database of 560 genodermatoses, with their phenotypic representations, affected organ systems and associated genes (see Supplementary Material) was previously compiled by expert analysis of OMIM database (Feramisco et al. 2009). The elementary phenotypic features were manually selected as general clinical manifestations that can occur independently in different diseases and, when combined, can cover phenotype of any included genodermatosis (Feramisco et al., 2009).

Correlation matrix $\mathbf{R}$ of elementary phenotypes is calculated based on the set of genodermatoses represented as vectors in the phenotype space:

$$R_{ij} = corr(P_i, P_j)$$

where $\mathbf{P} = \mathbf{X}^T$ is the matrix composed of phenotype vectors $\mathbf{P}_i$, that corresponds to the transposed matrix $\mathbf{X}$ of disease vectors $x_k = (x_{ki})$, $k = 1,N$ ($N$ is the dimension of phenotype space). $corr(\mathbf{P}_i, \mathbf{P}_j)$ is Pearson’s correlation coefficient of two vectors.

Principal components of the set of disease points in the phenotype space are derived as eigenvectors of covariance matrix $\mathbf{C} = \mathbf{XX}^T$, with largest
eigenvalues corresponding to the dimensions of strongest correlations within the data set X (Jolliffe, 2002).

Statistical significance of gene–phenotype associations is estimated from the observed counts of co-occurrence of a given phenotype with mutations in a given gene (Supplementary Tables S1–S5). Fisher’s exact test is used as a more appropriate alternative to chi square association test in the cases where counts in some cells of contingency tables are low (≤5). The significance level is adjusted for the multiple testing of all gene–phenotype associations using Bonferroni correction: \( \alpha = \alpha_0/n = 1.2 \times 10^{-5} \), where \( \alpha_0 = 0.05 \) and \( n = n(\text{genes}) \times n(\text{phenotypes}) \).

Phenotypic clustering is performed using UPGMA agglomerative method.

3 RESULTS

Using the Online Mendelian Inheritance in Man (OMIM) compendium of human mendelian inheritance (Amberger et al., 2009), we previously compiled a database of genetic skin diseases, their phenotypic representations, affected organ systems and associated genes (Feramisco et al., 2009). This database (see Supplementary Material) includes 560 diseases associated with 501 protein-coding genes, with ~16% of diseases linked to two or more mutated genes and 18% of genes linked to two or more disease entities.

3.1 Phenotypic categorization of genodermatoses

Based on the manual analysis of disease phenotypes, we define a minimal set of elementary phenotypic features whose combinations cover all included genodermatoses, so that phenotypic manifestation of each skin disease can be represented as a combination of several elementary features. This set includes 42 elementary dermatologic features forming 18 groups: cornification phenotypes, pigmentation phenotypes, etc. and 29 elementary systemic phenotypes forming 17 groups (Feramisco et al., 2009) (see Supplementary Material). For example, the group of pigmentation features includes hyper- and hypo-pigmentation, café au lait, poikiloderma and nevi (birthmarks and moles). Most of the genodermatoses are characterized by more than one elementary phenotype, with the average number of assigned elementary phenotypes being ~2.4 per disease (Feramisco et al., 2009). Distributions of the numbers of dermatologic and systemic phenotypes per disease and the numbers of diseases sharing an elementary phenotype are shown in Supplementary Figure S1.

As a combination of elementary features, each disease can be represented by a point in multi-dimensional space defined by 71 basis vectors corresponding to the features (Fig. 1). To check for the independence of these features in the phenotype space, we calculate their correlation matrix based on the set of all disease points (see ‘Methods’ section for details). This matrix (Fig. 2, see also Supplementary Material) does not show major correlation patterns in the incidences of different features in composite disease phenotypes. The highest non-diagonal correlation coefficient is 0.605 for poikiloderma versus alopecia/hypotrichosis phenotypes; the second highest is 0.505. When the distribution of disease points is analyzed in the plane (Supplementary Fig. S4A) or 3D-space (Supplementary Fig. S4B) of highest-correlated phenotypes, every possible combination of these phenotypes is found in a significant number of diseases.

In addition, we perform principal component analysis (PCA) of the disease set and visualize the distribution of points along principal components. Elongated or skewed distribution of points’ projections onto the subspace of first two or three principal components, which correspond to the largest correlations within the dataset, would indicate a major correlation in the occurrence of phenotypic features. Neither the projection on the plane of top two components (Fig. 2B) nor the projection in the space of top three components (Supplementary Fig. S2) reveal such correlations. The corresponding projections for the separate dermatologic and systemic phenotype sets, along with phenotype correlation matrices are shown in Supplementary Figure S3. These results suggest that our set of phenotypic features is largely independent.

In phenotypic space, the similarity between two diseases can be determined by the distance between the corresponding points (Fig. 1). We use these distances to group diseases by phenotypes. Several tested distance metrics (Manhattan block, Euclidean distance, etc.) produce similar results, thus we further use Euclidean distances for simplicity. The distances range from zero for disorders with the same sets of phenotypic features to 3.9 for the most distant disorders that have 15 elementary phenotype differences.

Based on this disease representation, we analyze (i) phenotypes shared among diseases associated with a protein or a group of proteins (Fig. 3A); and (ii) functional links between proteins associated with phenotypically similar diseases (Fig. 3B). This analysis can provide significant insights into molecular mechanisms of pathogenesis. First, associations between proteins and disease phenotypes can be dissected in a statistically rigorous manner and previously unknown links can be revealed. Second, similarity in phenotypic manifestation may suggest common mechanisms of action for different proteins or signaling systems, and point to potential functional interactions. Finally, inferred phenotypic association of a protein group or pathway provides a set of new protein candidates that may cause similar diseases of yet unknown molecular mechanism (Fig. 1).

Our approach is different from previously reported approaches to the representation of disease phenotypes (Lage et al., 2007; Robinson et al., 2008; van Driel et al., 2006) in two essential points. First, we base our analysis on the data of high quality, with the phenotype descriptions being manually curated by an expert. Second, as opposed to building ontology of all phenotypic terms
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3.2 Protein–phenotype associations

Decomposition of disease phenotypes into elementary features often reveals that an individual protein or a group of proteins is predominantly associated with a certain phenotypic feature (Fig. 3A). The statistical significance of such associations can be estimated from the frequencies of co-occurrence of mutations in a specific protein with an elementary phenotype. Our results confirm many previously known associations. For example, mutations in keratin I and collagens I and VII are significantly associated with disease phenotypes of hyperkeratosis (Supplementary Table S1, Fisher’s exact test P-value: $P = 1.1 \times 10^{-6}$), atrophy/aphasia/fragile skin (Supplementary Table S2, $P = 9.2 \times 10^{-8}$) and bullous epidermal cohesion (blistering phenotype, Supplementary Table S3, $P = 1.5 \times 10^{-9}$). In addition, our results suggest previously unknown associations. For example, the link between mutations in the subunits of laminin 5(332) and mucosal phenotype group (Supplementary Table S4, $P = 7.2 \times 10^{-3}$) has been detected. As a major component of the basement membrane, laminin 5(332) is an essential structural component of the dermal–epidermal junction and is involved in cell adhesion and signal transduction. Our analysis suggests that various defects in laminin 5(332) consistently affect the integrity of mucous membranes. Extending our analysis to groups of functionally related proteins, we find statistically significant
Table S5, P with PPP. Filled squares, proteins involved in TGF-
β pathway. Open squares, proteins associated with filament-associated proteins, or cell adhesion molecules. Caused by mutations in structural proteins (collagens, keratins), proteins may point to functional relationship between these proteins. For example, bullous (blistering) phenotype is mainly associated with a wide range of protein functions. However, some features are associated with more functionally uniform groups of proteins. For example, bullous (blistering) phenotype is mainly caused by mutations in structural proteins (collagens, keratins), filament-associated proteins, or cell adhesion molecules.

3.3 Functional associations between proteins through their phenotypic representation

Similarity of disease phenotypes caused by mutations of different proteins may point to functional relationship between these proteins. In addition to many known protein relations, our dataset allows for the inference of previously unknown functional links.

As an example, Figure 4 shows phenotypic clustering of telangiectasias (spider vein diseases) that suggests an association between the TGF-β cascade and the PPP. The cladogram based on phenotypic composition reveals two major groups of similar, tightly clustered diseases. The first group is associated exclusively with the proteins of DNA excision repair (ERCC2, ERCC6, DDB2, POLH), whereas the second group is associated with proteins that are connected to two distinct systems: TGF-β cascade (SMAD4, ENG, ACVR1) and PPP (transaldolase TALDO1 and glucose transporter GLUT10). Involvement of TGF-β in vascular anomalies has been reported for several diseases (Coucke et al., 2006; Loey et al., 2005; Tille and Pepper, 2004). The detected phenotypical similarity to the PPP-associated disorders suggests that PPP is implicated in angiogenesis through the same pathophysiological mechanism. In particular, we hypothesize a cross-talk between PPP and TGF-β cascade, which may mediate the connection between glucose metabolism and abnormal vascular development in angiopathies. Among other implications, this hypothesis provides a potential explanation of the known link between diabetes and angiopathies (Miles et al., 2007; Simo et al., 2006), as well as suggests new potential angiopathy-linked proteins.

4 DISCUSSION

The role of proteins and their interactions in the living organism is a central focus of molecular and cellular biology, with both fundamental and clinical implications. In this respect, the cataloged links between protein mutations and their phenotypic manifestations in disease are, in a sense, the results of a grand mutagenesis ‘experiment’ that may prove useful for finding new associations and generating new hypotheses. Here, we present an analysis of phenotypes expressed in genetic skin disorders and the corresponding causative genes.

Although our method involved initial manual curation of elementary phenotypes, it can be readily generalized to other disease sets with available phenotype descriptions. The construction of the set of elementary phenotypes can start from all phenotypic terms derived from textual annotations of diseases of interest, further filtered by manual expert analysis and/or numerical selection of the maximal subset of independent phenotypic features, based, for example, on the analysis of correlation matrix (Fig. 2A) or on PCA. However, we believe that the set of phenotypes manually curated by an expert provides a more informative categorization, since it (i) involves additional knowledge not reflected in the brief disease annotations; and (ii) is based on well-defined clinical terms and thus is more accessible and relevant for clinical research community.

As an example, analysis of such a dataset can link genes to phenotype-based prediction of potential proteins involved in similar molecular mechanisms of disease; (iii) hypotheses about phenotypic effects of mutations in functionally related proteins; and (iv) phenotype-based prediction of potential proteins involved in similar diseases with unknown genetic causation.

The presented protein-phenotype associations, inferred from a relatively restricted statistical sample of OMIM, can be validated on larger datasets. This validation may be performed in at least two directions. First, phenotypic effects of mutations in a specific gene can be analyzed on a wider scale: most directly, in larger...
Park\textit{et al.} example, PPP enzyme glucose-6-phosphate dehydrogenase is shown 
suggested by phenotypic clustering of telangiectasias (Fig. 4).

Utilizing glucose-6-phosphate as the substrate, PPP produces the major fraction of cell’s NADPH, which plays a central role in 
maintaining intracellular redox potential by serving as a co-
factor in the reduction of glutathione (Berg\textit{et al.}, 2001). As an 
extreme, PPP enzyme glucose-6-phosphate dehydrogenase is shown 
to play an important role in oxidative stress (Leopold, 2003; 
Park\textit{et al.}, 2006), which is thought to be the main mechanism 
of its involvement in cardiovascular disease (Matsui\textit{et al.}, 2005; 
Rajasekaran\textit{et al.}, 2007; Wiesenfeld et al., 1970). Changing the 
concentration of reduced glutathione alters redox state and affects, 
among other systems, TGF-β pathway (Maulik and Das, 2002; Shm 
\textit{et al.}, 1994). Altered redox state and the resulting oxidative stress 
are known to stimulate angiogenic response (Maulik and Das, 2002; 
Usui-Fukai, 2006), and are shown to be involved in at least one 
disease or with telangiectasia phenotype (Nicotera et al., 1989). In 
addition, the effect of GLUT10 deficiency on TGF-β signaling in 
the arterial wall is shown in arterial tortuosity syndrome (Coucke 
\textit{et al.}, 2006).

We hypothesize that (i) defects in PPP may cause abnormal 
vascular development by altering intracellular redox state; and (ii) 
this effect may be mediated by TGF-β signaling cascade. This 
hypothesis has several important implications. First, the reported 
effects of glucose concentration on TGF-β cascade (Hua et al., 2003; 
Isom\textit{et al.}, 2000; Zhu\textit{et al.}, 2007) may be mediated by PPP. 
Furthermore, our hypothesis may explain the observed connection 
between microangiopathies and diabetes (Miles\textit{et al.}, 2007; Simo 
\textit{et al.}, 2006), suggesting that abnormal angiogenesis may be caused 
by changes in PPP activity due to the disruption of intracellular 
glucose homeostasis. Finally, our hypothesis suggests that other 
proteins of PPP, as well as of TGF-β pathway, may be associated 
with angiopathies, providing a new set of potential candidates for 
molecular analysis and drug targeting.

This hypothesis can be readily tested in various experiments, 
including (i) analysis of redox-state and TGF-β responses to 
different levels of glucose concentration in the patients with 
telangiectasia phenotype carrying TALDO1 and GLUT10 
mutations, or in corresponding animal models; (ii) analysis of 
these responses, as well as general phenotypic effects caused by 
mutations in other PPP proteins (in animal models or clinical 
studies); (iii) analysis of TGF-β response to expression changes or 
up- and down-regulation of PPP proteins in vivo and in culture; 
(iv) sequencing genes of PPP and TGF-β pathway in patients with 
telangiectasias of unknown genetic background; and (v) further 
experimental investigation of the role of PPP activity in the 
association between angiopathies and diabetes, in diabetes patients 
and animal models.

In conclusion, our manually curated decomposition of disease 
phenotypes is based on the set of elementary phenotypic features 
that serve as basis vectors in a multidimensional space, as opposed 
to previously reported automated (Lage\textit{et al.}, 2007; van Driel 
\textit{et al.}, 2006) or semi-automated (Robinson\textit{et al.}, 2008) ontologies 
of phenotypic terms. The potential value of this approach is 
shown by confirming known and revealing previously unknown 
gene–phenotype, gene–gene and pathway–pathway associations.

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**REFERENCES**

Antibolsg, J. et al. (2009) McKusick’s Online Mendelian Inheritance in Man (OMIM). 
Nucleic Acid Res., 37, 3279–32796.

Berg, J. L. et al. (2001) Biochemistry. W.H. Freeman & Co, New York.

Coucke, P. J. et al. (2006) Mutations in the faciliative glucose transporters GLUT10 alter 
angiogenesis and cause arterial tortuosity syndrome. Nat. Genet., 38, 452–457.

Furrwicz, J. D. et al. (2009) Phenotypic and genotypic analyses of genetic skin 
disease through the online Mendelian inheritance in man (OMIM) database. J. Invest. 
Dermatol., (Epub ahead of print, doi: 10.1038/jid.2009.108)

Goh, K. L. et al. (2007) The human disease network. Proc. Natl Acad. Sci. USA, 104, 
8685–8690.

Hua, H. et al. (2003) High glucose-suppressed endothelium-1 Ca2+ signaling via NADPH 
oxidase and diacylglycerol-sensitive protein kinase C isotypes in mesangial cells. 
J. Biol. Chem., 278, 33951–33962.

Isom\textit{et al.} (2000) Stimulation of TGF-beta type II receptor by high glucose in 
mouse mesangial cells and in diabetic kidney. Am. J. Physiol. Renal Physiol., 278, 
F830–F838.

Jolliffe, I. T. (2002) Principal Component Analysis. Springer, New York.

Lage, K. et al. (2007) A human phenotype-interaction network of protein complexes 
implicated in genetic disorders. Nat. Biotechnol., 25, 809–316.

Leopold, J. A. et al. (2003) Glucose-6-phosphate dehydrogenase upregulation 
decreases endothelial cell oxidant stress and increases bioavailable nitric oxide. 
Arterioscler. Thromb. Vasc. Biol., 23, 411–417.

Lorey, B. L. et al. (2005) A syndrome of altered cardiovascular, cranofacial, 
neurocognitive and skeletal development caused by mutations in TGFBR1 or 
TGFBR2. Nat. Genet., 37, 275–281.

Maulik, R. et al. (2005) Glucose-6-phosphate dehydrogenase deficiency decreases 
the vascular response to angiotensin II. Circulation, 112, 257–263.

Maulik, N. and Das, D. K. (2002) Redox signaling in vascular angiogenesis. Free Radic. 
Biol. Med., 33, 1047–1060.

Miles, P. D. et al. (2007) Impaired insulin secretion in a mouse model of ataxia 
telangiectasia. Am. J. Physiol. Endocrinol. Metab., 293, E70–E74.

Nistler, T. M. et al. (1989) Elevated superoxide dismutase in Bloom’s syndrome: a 
genetic condition of oxidative stress. Cancer. Res., 49, 5230–5234.

Park, J. et al. (2006) Increase in glucose-6-phosphate dehydrogenase in adipocytes 
stimulates oxidative stress and inflammatory signals. Diabetes, 55, 2939–2949.

Rajasekaran, N. S. et al. (2007) Human alpha B-crystallin mutation causes oxido-
reductive stress and protein aggregation cardiomyopathy in mice. Cell, 130, 427–439.

Robinson, P. N. et al. (2008) The Human Phenotype Ontology: a tool for annotating 
and analyzing human hereditary disease. Am. J. Hum. Genet., 83, 610–615.

Roberts, A. et al. (2007) Probing genetic overlap among complex human phenotypes. 
Proc. Natl Acad. Sci. USA, 104, 11694–11699.

Shan, Z. et al. (1994) Intracellular glutathione influences collagen generation by 
mesangial cells. Kidney Int., 46, 388–395.

Simo, R. et al. (2006) Angiogenic and antiangiogenic factors in proliferative diabetic 
retinopathy. Curr. Diabetol. Rev., 2, 71–88.

Tillet, J. C. and Pepper, M. S. (2004) Hereditary vascular anomalies: new insights into their 
pathogenesis. Arterioscler. Thromb. Vasc. Biol., 24, 1574–1589.

Usui-Fukai, M. (2006) Redox signaling in angiogenesis: role of NADPH oxidase. 
Cardiovasc. Res., 74, 226–233.
van Driel, M.A. et al. (2006) A text-mining analysis of the human phenome. *Eur. J. Hum. Genet.*, 14, 535–542.

Wiesenfeld, S.L. et al. (1970) Elevated blood pressure, pulse rate and serum creatinine in Negro males deficient in glucose-6-phosphate dehydrogenase. *N. Engl. J. Med.*, 282, 1001–1002.

Wu, X. et al. (2008) Network-based global inference of human disease genes. *Mol. Syst. Biol.*, 4, 189.

Zhu, Y. et al. (2007) Regulation of transforming growth factor beta in diabetic nephropathy: implications for treatment. *Semin. Nephrol.*, 27, 153–160.