Tissue-specific regulatory elements in mammalian promoters:

Supplementary information

To identify mammalian tissue-specific elements we (1) identify transcripts with tissue-specific expression, (2) map transcripts to proximal promoters, and (3) analyze promoters to identify common binding site motifs and cis-regulatory modules. Our approach builds on previous work to identify motifs in promoters of co-expressed transcripts. Co-regulated transcripts (*e.g.* tissue-specific) are likely to be controlled by similar machinery. We identify common motifs and modules that distinguish promoters of tissue specific transcripts from other promoters.

1 Transcripts and promoters under tissue-specific regulation

We considered transcripts tissue-specific if they play a special role in a specific tissue or small set of tissues. Tissue-specificity is a function of regulation, and a particular transcript may be expressed or even specific to more than one tissue. We assumed that tissue-specific function is associated with tissue-specific regulation.

To build sets of tissue-specific transcripts, we combined information from GNF SymAtlas (Su et al., 2004) (for both human and mouse), the Hughes Toronto microarrays (Zhang et al., 2004b) (for mouse), EST data from dbEST (Boguski et al., 1993) and membership in specific GO categories (Ashburner et al., 2000). We used key-word searches in the NCBI Nucleotide database and the Eukaryotic Promoter Database (EPD) (Perier et al., 1998) for guidance only.

We used multiple data sources to circumvent problems associated with each individual source, and add robustness to tissue-specific transcript selection. For example, expression of certain transcripts in dbEST may only have been measured for a small number of tissues, and are not a robust indicator of specificity. The GNF microarray data includes two replicates. Ignoring highly variable observations within and between replicates leads to incomplete data; considering such observations is equally problematic. Multiple sources of information were combined using a voting system, and each source contributed at most one vote. We showed that orthologs of transcripts with multiple votes for tissue-specific regulation are significantly more likely to have evidence for tissue-specific regulation, even when Gene Ontology votes were discarded. Because ortholog information did not have a vote for tissue specificity, significantly more frequent verification by comparative genomics suggests that selection according to multiple evidence is more reliable.

The construction of tissue specific sets is a complex and error prone task. Voting systems need to minimize dependence between annotation sources, are sure to pass over tissue specific transcripts because of inconclusive evidence, and should treat paralog transcripts with special care. Because of varying data type and experiment quality, we varied thresholds used for assigning votes to evidence. As additional sources of expression information become available and experiment quality become more uniform, thresholds used to assign votes will become standard. One example for possibly erroneous tissue-specific annotation is evident in the mouse pancreas set, where 11 genes from the Klk family received a vote and were included in the tissue specific set. The votes originate from membership is a pancreas-related GO function, which was annotated for the human ortholog (the mouse genes share the same ortholog). We had no expression-based evidence for pancreas-specific regulation in our mouse data. The genes are highly similar and may be the product of a recent duplication. None of our mouse-pancreas-specific motifs or modules were identified in the Klk promoters, and their inclusion increased our error estimates.

1.1 microarray data

Because most of the probes called present in the experiments are associated with RefSeq transcripts, and because in general our characterization of promoters and first introns is better for RefSeqs than other annotations (almost 100% of experimentally verfied promoters have RefSeq annotations), we decided to focus exclusively on RefSeq transcripts (see Table 11). Moreover, there is evidence that expression of different transcripts in different tissues is widespread (Fuchs et al., 1999; Johnson et al., 2003; Zhang et al., 2004a), and that different transcripts can have different first exons, and hence different promoters (Yamashita et al., 2006).

To associate probes with RefSeq transcripts, we mapped the probes back to the genomes (NCBI human genome assembly Hs33 and mouse genome assembly v3C dating to February 2003 for GNF and Mm5 for the Hughes Toronto array) to identify the probe locations and exon targets. GNF and GeneNote probes (Affymetrix gene chips) are 25 bases long and probe-transcript mappings were required to be perfect matches. The Hughes Toronto array probes are 40-bases long and mappings were required to have 39 base matches. Probes that matched more than 3 DNA targets were discarded. We chose this simple criteria as a compromise between data loss and quality. Using multiple probes per transcript and repeated experiments on the same tissue samples allows for correcting imprecise expression intensity measurements for a particular transcript target. We used the resulting probe-to-exon map to identify the RefSeq transcripts targeted by each probe, and assign a probe set to each transcript.

Probes with detection ability that is not substantially different than the corresponding mismatch probe are suspect. To obtain A/P calls for the transcripts, we used the A/P calls of the corresponding probe sets. If in a particular tissue the probe set A/P calls disagreed, we removed the transcript from further consideration, otherwise we called the transcript *present* or *absent*. The number of excluded transcripts due to this pruning operation ranged from under 5% to 80% of potential tissue-specific transcripts. 285 transcripts had unusually high intensity level (above 3 standard deviations from mean) in the GNF data for human skeletal muscle. 227 (80%) of these were rejected because of A/P calls. 58 of the 227 were reinstated because of evidence from other experiments. Obtaining intensities and p-values for a transcript is more straight-forward: we took the mean intensity and geometric-mean p-value of its corresponding probes.

To identify transcripts with unusually high intensity in few tissues, we calculated the mean and standard deviation of of the normalized intensity across all experiments (for the GNF data mouse and human are evaluated separately). For the GNF and GeneNote data, we considered transcripts that are called present and have intensity greater than three standard deviations from the mean intensity to be specific. For the Hughes Toronto array, where variability between probe reads is higher, we called transcript specific if their normalized intensity was greater than 2 and greater than ten standard deviations from the mean, and they were called present. The Hughes Toronto array did not include experiments for mouse CD4 T-cells, and GeneNote did not include experiments for human CD4 T-cells and testis.

1.2 EST Data

dbEST is a depository for expressed sequence tags, maintained by NCBI (Boguski et al., 1993). When ESTs are derived from specific tissues, this information is specified in dbEST. Because of the nature of tissue sample collection, source variability, and because most ESTs are derived from tissue cocktails and not all experiments are focused on keeping tissue purity, dbEST tissue classification may be imprecise. However, when multiple EST libraries describe a particular gene as expressed in a particular tissue and this gene was detected in few other tissues, we considered the dbEST evidence strong enough to cast votes for tissue specificity. We considered evidence for tissue specificity of a gene as evidence for all alternative

transcripts of this gene. For a dbEST vote in a given tissue, at least 3 EST libraries had to describe expression observation in this tissue, and more than 50% of tissue-related observations had to be in this tissue.

1.3 GO Terms

We associated a set of GO Terms with each tissue. This was done by compiling a set of keywords for each tissue (*e.g.* "renal" was associated with Kidney), and searching GO Term names and definitions for those keywords. For each tissue, we produced a set of GO Terms that were subsequently reviewed to ensure that the context of the keywords was appropriate. Each gene annotated with at least one GO Term associated with a tissue received one positive vote for specificity in that tissue. Similarly to EST evidence, we considered each point of evidence for a gene as evidence for all alternative transcripts of this gene.

1.4 Identifying factors expressed in tissues

To assist interpretation of results we assembled factors with evidence of expression in each tissue according SymAtlas, Hughes Lab, GeneNote and dbEST data. These lists are available in TCat. A transcript was considered expressed in a microarray experiment if it received a present call, regardless of intensity values. For dbEST, a transcript was considered expressed if any associated ESTs were observed at least once in that tissue.

1.5 Transcripts with strong evidence for tissue-specific regulation

In all tissues except CD4 T-cells, orthologs of transcripts with multiple votes for tissue-specific regulation were more likely to have evidence for specific regulation in that tissue. This suggests that the false-positive rate for calling a transcript tissue-specific is much lower when based on multiple votes. To compare the predictive power of orthologs, we assembled all pairs of transcripts and their orthologs, where at least one member had evidence for tissue-specific regulation. Every transcript appeared in only one pair, and transcripts with no known ortholog were eliminated. The pairs can be partitioned into 2 sets, those pairs that include a transcript with multiple votes and those who do not. We then used a hypergeometric fixed marginal contingency table test (Fisher exact) to compare the proportion of pairs (in each of the two sets) where each of the transcripts had evidence for tissue-specific regulation. The fixed marginal contingency table p-value follows the hypergeometric distribution (Agresti, 1992). The two-sided p-value for the table is the sum of the probabilities of all tables that are at least as extreme.

In the main body of the paper we gave the list of genes and orthologous transcripts with multiple votes for skeletal muscle-specific regulation in both human and mouse. Here, in Tables 5 to 10 we give the corresponding lists for the other 6 tissues. Note that each promoter set included 100 promoters, including some promoters that correspond to transcripts with only one vote for tissue-specific regulation. The distribution of votes per transcript in the set corresponding to analyzed promoter sets is given in Figure 3.

1.6 Obtaining promoter sequences

Regulatory elements can exist almost anywhere in the genome, but they are highly concentrated in proximal promoters. In past work (Smith et al., 2005b,a) we have been successful at identifying previously characterized motifs for factors known to play tissue-specific regulatory roles. Promoter quality (*i.e.* confidence in the transcription start site) has a large impact, and poor quality promoters may hurt motif discovery even more than poor quality sets of tissue specific transcripts (*e.g.* those containing ubiquitous or incorrectly assigned transcripts).

Figure 3. The distribution of votes per transcript corresponding to analyzed promoters sets. Each set included 100 promoters, and each promoter corresponded to a transcript with evidence for tissue specific regulation from possibly 0 to 4 sources. We display the number of transcripts $(y\text{-axis})$ with the given number of votes for tissue-specific regulation (x-axis). Distribution that are skewed to the left describe promoter sets with weaker evidence for tissue-specific regulation, and those that are skewed to the right describe promoter sets with stronger evidence.

Table 5. Transcripts with multiple votes for liver-specificity in both human and mouse. The "Votes" column gives the total number of votes for liver-specificity in both human and mouse.

Table 6. Transcripts with multiple votes for CD4 T cells-specificity in both human and mouse. The "Votes" column gives the total number of votes for CD4 T cells-specificity in both human and mouse.

Symbol	Name	Human RefSeq	Mouse RefSeq	Votes
MYL7	myosin, light polypeptide 7, regulatory	NM 021223	NM 022879	
CSRP3	cysteine and glycine-rich protein 3 (cardiac LIM protein)	NM 003476	NM 013808	₆
CASQ ₂	calsequestrin 2 (cardiac muscle)	NM 001232	NM 009814	h
TNNT ₂	troponin T type 2 (cardiac)	NM 000364	NM 011619	
NKX2-5	NK2 transcription factor related, locus 5 (Drosophila)	NM 004387	NM 008700	
MYBPC3	myosin binding protein C, cardiac	NM 000256	NM 008653	
ACTC	actin, alpha, cardiac muscle	NM 005159	NM 009608	
S ₁₀₀ A ₁	S100 calcium binding protein A1	NM 006271	NM 011309	
RYR ₂	ryanodine receptor 2 (cardiac)	NM 001035	NM 023868	
MYOZ2	myozenin 2	NM 016599	NM 021503	
MFN2	mitofusin 2	NM 014874	NM 133201	

Table 7. Transcripts with multiple votes for heart-specificity in both human and mouse. The "Votes" column gives the total number of votes for heart-specificity in both human and mouse.

Table 8. Transcripts with multiple votes for kidney-specificity in both human and mouse. The "Votes" column gives the total number of votes for kidney-specificity in both human and mouse.

Table 9. Transcripts with multiple votes for pancreas-specificity in both human and mouse. The "Votes" column gives the total number of votes for pancreas-specificity in both human and mouse.

Table 10. Transcripts with multiple votes for testis-specificity in both human and mouse. The "Votes" column gives the total number of votes for testis-specificity in both human and mouse.

Table 11. Summary of promoter data.

The main resource for mapping transcripts to promoters is the CSHL mammalian promoter database (CSHLmpd) (Xuan et al., 2005), which includes human, mouse and rat. CSHLmpd includes experimentally confirmed promoters that are annotated in EPD (Perier et al., 1998), DBTSS (Suzuki et al., 2002) and GenBank, as well as computationally predicted promoters. All but 27 transcripts with an experimentally verified transcription start site (TSS) correspond to RefSeqs (see Table 11 for CSHLmpd statistics). may be associated with the same TSS.

Repetitive regions in promoters. Human and mouse proximal promoters contain a high proportion of LINEs (Human), SINEs and simple repeats. Repeats were not masked for most of our analysis. If tissuespecific promoters have no special relation with any particular kind of repeat, the repeats will have no effect on our analysis because we measured enrichment of motifs and modules relative to background sets composed of real promoters, and not simplified statistical models. Repeat regions make a considerable portion of the nucleotide content of our foreground-set promoters. Using RepeatMasker (Bedell et al., 2000) to mask primate and rodent repeats in the human and mouse tissue-specific promoters indicates that 12% to 26% of the nucleotides are within repeat regions. The breakdown per tissue is given in Table 12.

CpG-related promoters. Vertebrate promoter sequences are enriched with CpG islands and these are often used to help identify promoters. CpG islands tend to occur with higher frequency in promoters of housekeeping genes than tissue-specific genes (Gardiner-Garden and Frommer, 1987). Because CpG island frequency is related to tissue-specific transcription, we calculated CpG frequency and GC-content in our promoter sets. The Gardiner-Garden method (Gardiner-Garden and Frommer, 1987) requires CpG islands to have GC-content at least 0.50, length greater than 200bp, and number of CpG dinucleotides at least 0.6 times the number expected based on the GC-content. The Takai method (Takai and Jones, 2002) refines the Gardiner-Garden method with attention to detection of human CpG islands. We say that a promoter is CpG

Tissue	Human	Mouse
CD4 T-cells	20.22%	16.55%
Heart	15.96%	10.71%
Kidney	17.21%	15.47%
Liver	22.77%	16.09%
Pancreas	22.23%	18.24%
Skeletal muscle	11.73%	12.61%
Testis	25.76%	17.40%

Table 12. Proportions of RepeatMasker-masked nucleotides from total promoter length.

Table 13. Proportion of CpG related promoters in our tissue specific sets and in a set corresponding to ubiquitous transcripts (house keeping).

related if a CpG island is detected less than 2000 bases upstream or 500 bases downstream from the TSS. To compare the proportion of CpG related promoters in our tissue-specific sets to the proportion of of CpG related promoters of house keeping genes we selected transcripts with EST evidence in multiple tissues. In both mouse and human we ranked transcripts to minimize the proportion of EST evidence in any given tissue, and selected the top 1000. Table 13 gives a comparison between CpG related promoters in these sets and CpG related promoters in tissue specific sets.

1.7 Tissue-expressed transcription factors

We attempted to identify transcription factors that are expressed in a given tissue using the same data used to identify tissue specific sets. This data includes GNF SymAtlas, the Hughes Toronto array, and EST data from dbEST. We were interested in expression evidence and were not concerned with tissue-specificity, however attempts to identify expression of a single transcript are fundamentally different than attempts to construct transcript sets. The former require each transcript to have strong evidence, while the later are robust to outliers and are evaluated as a set. For this reason we elected not use the GO annotation for calling tissue-specificity of single transcripts. Due to data and analysis constraints, we did not require multiple confirmations for factor expression and simply described the evidence for each factor in TCat. The highest confidence data had multiple votes, few absent calls from the microarray expression data, and high proportion in the given tissue according to dbEST.

2 Motifs and redundancy elimination

Previously characterized motifs were taken from the vertebrate subset of the matrix table of TRANSFAC version 9.1 (Matys et al., 2003). We used UNIQMOTIFS (Smith et al., 2005c) to eliminate redundancies in the presentation. A motif was considered redundant if it was similar to a higher ranked motif, and similarity was measured using the Kullback-Leibler divergence between position frequency matrices (Smith et al., 2005b). We associated redundant motifs with the highest ranking similar non-redundant motif.

2.1 Significance of ranks for known motifs

The identities of known tissue-specific regulators along with a characterization of their binding sites, can be used to verify our ranking method. Skeletal muscle and liver are well studied (Odom et al., 2004; Krivan and Wasserman, 2001; Wasserman and Fickett, 1998; Johnson et al., 2005), and the transcription factors known to have large functional roles in these tissues are well characterized. In liver, the most important factors are known to be HNF-1, HNF-3, HNF-4, C/EBP, VDR and CDP (Schrem et al., 2002, 2004). In skeletal muscle, the most important factors are known to be MEF-2, SRF, PAX, and members of the Myogenin family (Duprey and Lesens, 1994). We used the Wilcoxon signed ranks test to determine if the ranks of the matrices associated with these factors received significantly high ranks when the entire set of 554 vertebrate matrices from TRANSFAC (release 9.1) were ranked according to importance.

There were a total of 37 matrices for liver, the sum of their ranks was 2574, and the associated p-value was 1.38×10^{-15} . There was also a total of 37 matrices for skeletal muscle, with a rank sum of 5115.5 and an associated *p*-value of 6.07×10^{-8} .

2.2 Models and significance of motifs and modules.

We used position-weight matrices to model transcription factor binding sites, and top-scoring sites in each promoter to measure motif enrichment, but these are not always appropriate. For example, the POU3 family of factors bind to a pair of sites that can be separated by up to three nucleotides (Li et al., 1993). Such motifs cannot be accurately described using position-weight matrices, and we expect that large classes of factors will be identified with binding specificity that is poorly characterized by position-weight matrices. Recent results show that true binding sites for certain factors are often accompanied by nearby lower-affinity sites (Zhang et al., 2006), and for such factors this information should be considered when evaluating motif enrichment.

Modeling the organization of regulatory modules is a formidable challenge. Some experimental evidence suggest that conserved relative spacing and orientation between module sites is important, while other evidence suggest the opposite; it is likely that no single organization model can adequately describe all modules (Erives and Levine, 2004). We did not use conservation of order, spacing or orientation to reverse engineer modules, but believe that in many cases co-linear order is conserved on the module level. Our method for identifying modules required that each component (*i.e.* motif) in the module contribute significantly to the quality of the module, which provides statistical evidence for functional interaction between all motifs in the module. We found that the pairing of myogenin family members with SRF or MEF-2 produces significant modules, but pairing of MEF-2 and SRF is not significantly enriched in skeletal-muscle specific promoters. This finding suggests that MEF-2 and SRF regulate transcription in skeletal muscle independently. We note that computational identification of module component sites is especially challenging and depends on interactions between the components. In present work, when several possible sites of variable affinity were predicted, we chose to annotate only the top-scoring sites.

Program	Width Bits Gran. Refine				N.
DME		12 1.55	0.5	0.25	25
	10	1.6	D	0.125	50
	8	1.8	Ð	0.125	50
$DME-B$	10	16	0.5	0.25	25
		18	Ð	0.125	50

Table 14. Parameters used for runs of DME and DME-B to discover motifs *de novo* that are enriched in the tissue-specific promoter sets relative to the background sets. The *Bits* value refers to bits per column, the *Gran.* value refers to the granularity, the *Refine* value describes the parameter of the refinement procedure, and the N value is the number of motifs requested. More information on these parameters can be found in (Smith et al., 2005b)

Binding specificity for some transcription factors may be poorly characterized. Examples include characterizations based on too few sites, and *in vitro* verification in cell-lines where a factor has a different conformation or affinity for a particular site. An example of a factor with possibly incomplete characterization of binding specificity is HNF-6. Our data did not include evidence for its expression in liver but HNF-6 is a known liver regulator (Samadani and Costa, 1996), whose TRANSFAC motif was not found to be enriched in our liver promoter sets. The HNF-6 binding motif was derived from a small set of sites identified in a restricted context (Samadani and Costa, 1996; Lannoy et al., 1998), and other evidence suggests that HNF-6 has two modes of binding to DNA (Lannoy et al., 1998).

2.3 Motifs identified *de novo*

Motifs discovered *de novo* were obtained using the DME (Smith et al., 2005b) and DME-B (Smith et al., 2006) algorithms. We used the parameter sets in Table 14. Redundant motifs were combined with the nonredundant one to which they were associated, and the combination was optimized greedily with respect to the balanced error rate. The program used to combine the motifs and optimize with respect to motif importance is available from the authors. When a *de novo* identified motif M was similar to an experimentally verified motif M' , we annotated M with the factor that is known to bind sequences matching M' . Similarity was measured using Kullback-Leibler divergence (Kullback and Leibler, 1951), using MATCOMPARE (Schones et al., 2005) (available in CREAD), and motifs M and M' of length $m \le m'$ were called similar if the motifs could be aligned in at least $m - 1$ positions without gaps with K-L divergence below 1.0.

2.4 Motif rank and order correlation between human and mouse

To measure correlation between the tissue-specific regulatory apparatus in human and mouse, we compared single motif ranks. This comparison method is largely independent of sequence similarity and ortholog information, and is used to compare over- and under-representation of motifs in our foreground sets. Motif ranking summarizes known information in each foreground set, and is therefore ideal for measuring regulatory correlation. We used the Spearman rank correlation test (Altman, 1991) to compare vertebrate motif ranks in human and mouse. We found significant correlation in all but CD4 T-cells (Table 15).

To test whether the correlation can be detected using standard sequence alignment methods, we identified the highest likelihood sites for the vertebrate motif set in each proximal promoter and its ortholog, and compared the order of the sites in the pair using a Wilcoxon signed-ranks test. When the top score

m. Tissue	TD4 T-cells	Pancreas	m. restis	Kidney	Skeletal muscle	∟iver	Hear
p -val	0.0618	. .49E-07	$5.63E-12$	3.87E-12	$19F-7$	10E-29	46E-. b.

Table 15. Correlation between vertebrate motif ranks in human and mouse tissues.

was shared by multiple sites we chose the site that best matched the ortholog order. We noticed that promoters with significant co-linear site conservation also had high sequence similarity. We measured similarity as the proportion of nucleotides matched by a clustal w alignment. Our data included 1, 17, 6, 12, 15, 40, and 11 ortholog promoters for pancreas, testis, kidney, skeletal muscle, liver, and heart, respectively. Sequence similarity over the 102 promoter pairs was 0.51 ± 0.079 , which is significantly higher than random promoter pairs (0.411 \pm 0.022), and 9 pairs were found to have significant co-linear site conservation. In testis, the proximal promoter for PHD finger protein 7 (PHF7) (NM_027949 and NM_016483) had significant co-linear conservation; the similarity between the promoters was 0.65. In kidney, solute carrier family 27 (SLC27A2) (NM_003645 and NM_011978) with 0.49 similarity. In skeletal muscle, troponin C type 2 (TNNC2) (NM_003279 and NM_009394) with 0.61 similarity, and myogenic factor 6 (MYF6) (NM_002469 and NM_008657) with 0.76 similarity. In liver, argininosuccinate synthetase (ASS) (NM_000050 and NM_007494) with 0.56 similarity, and lecithin-cholesterol acyltransferase (LCAT) (NM_008490 and NM_000229) with 0.70 similarity. In heart, mitofusin 2 (MFN2) (NM_133201 and NM_014874) with 0.42 similarity, ryanodine receptor 2 (RYR2) (NM_001035 and NM_023868) with 0.47 similarity, and actin alpha cardiac muscle (ACTC) (NM_009608 and NM_005159) with 0.68 similarity. The result suggests that only a small proportion of the highest-likelihood ortholog sites can be recovered using traditional multiple sequence alignment.

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