# **AN INTEGRATIVE GENE-EXPRESSION ANALYSIS OF AXOLOTL LIMB WOUND HEALING AND REGENERATION**

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF ENGINEERING AND NATURAL SCIENCES OF ISTANBUL MEDIPOL UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN

BIOMEDICAL ENGINEERING AND BIOINFORMATICS

By Mustafa SİBAİ June, 2019

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We certify that we have read this thesis and that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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## ABSTRACT

# AN INTEGRATIVE GENE-EXPRESSION ANALYSIS OF AXOLOTL LIMB WOUND HEALING AND REGENERATION

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### M.S. in Biomedical Engineering and Bioinformatics

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#### June, 2019

Axolotl is a member of the urodele amphibians that exhibits extraordinary regenerative and scarless wound healing capabilities, fully restoring a lost limb as well as efficiently healing a damaged one. Axolotl has recently been used as a powerful experimental model for the fields of regenerative biology and medicine. Several studies have employed high-throughput, omics-based approaches to uncover the regenerative cues of the axolotl limb *en masse*. Microarrays and RNA-Sequencing technologies have been the most commonly used transcriptomic tools for detecting differentially expressed (DE) genes in different phases of the regenerating limb. Although those studies have found many important genes and pathways that are implicated in the regenerative process, the obtained results may lack sufficient consistency due to study designs originating from different labs, which undermines the statistical power of their experiments. Therefore, to bridge this statistical gap, the aim of this thesis was to perform an integrative analysis of publicly available microarray and RNA-Seq data from Axolotl limb samples having comparable study designs. Three biological groups were conceived for the analysis; control group (intact tissue), wound healing group (up to around 50 hours post amputation), and regenerative group (from 50 hours to 28 days post amputation). Cross-platform normalization (merging) method was selected for separately performing the integrative analysis of microarray and RNA-Seq data from Axolotl limb samples. Differential expression analysis was separately carried out using the R/Bioconductor "limma" package after processing data from both technologies. We found 91 genes, 351 genes, and 280 genes as the top DE genes which showed adjusted p <0.01 from data of both technologies in wound healing vs. control, regenerative vs. control, and regenerative vs. wound healing, respectively. Detailed analyses showed consistent correlation of the logarithmic fold changes of the differentially expressed genes distributed among the biological comparisons, within and between both technologies. Gene ontology annotations demonstrated concordance with the literature on the biological processes involved in the axolotl limb wound healing and regeneration. Future studies on axolotl limb regeneration may benefit from the utilized methodology for enhanced statistical power and more consistent results.

*Keywords: axolotl, wound healing, regeneration, merging, differential expression*.

# **ÖZET**

# AKSOLOTL YARA İYİLEŞMESİ VE REJENERASYONUNUN İNTEGRATİF GEN EKSPRESYON ANALİZİ

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Aksolotl, üstün rejeneratif ve hasarsız yara iyileşme kabiliyeti sergileyen, kaybedilen ve zarar görmüş olan bir uzvu tamamen ve etkin bir şekilde iyileştiren ürodele amfibilerinin bir üyesidir. Aksolotl yakın zamanda rejeneratif biyoloji ve tıp alanlarında güçlü bir deneysel model olarak kullanılmaya başlanmıştır. Bazı çalışmalarda, aksolot uzuvunun rejeneratif ipuçlarını topluca açığa çıkarmak için yüksek verimli, omik tabanlı yaklaşımlar kullanılmıştır. Mikrodizi analizi ve RNA sekanslama teknolojileri, rejenere olan uzuvun farklı fazlarında diferansiyel olarak eksprese edilen (DE) genleri tespit etmek için en yaygın kullanılan transkriptomik araçlardır. Her ne kadar bu çalışmalar ile rejeneratif süreçte yer alan birçok önemli gen ve yolak bulunmuş olsa da, elde edilen sonuçlar, farklı laboratuarların çalışma tasarımları nedeniyle deneylerinin istatistiksel gücünü zayıflatıp sonuçların tutarlılığını etkileyebilmektedir. Bu tezin amacı bu istatistiksel açığı kapatmak için, halka açık mikroarray ve RNA-Seq aksolotl verilerinin bütünleştirici bir analizini yapmaktır. Analiz için üç biyolojik grup tasarlanmıştır; kontrol grubu (sağlam doku), yara iyileşme grubu (amputasyondan sonra yaklaşık 50 saate kadar) ve rejeneratif grup (amputasyon sonrası 50 saat ile 28 gün arası). Mikroarray ve RNA-Seq verilerinin bütünleştirici analizini ayrı ayrı yapmak için çapraz platform normalleştirme (birleştirme) yöntemi seçilmiştir. DE analizi, her iki teknolojiden veri işlendikten sonra R / Bioconductor "limma" paketi kullanılarak ayrı ayrı gerçekleştirildi. Yapılan karşılaştırmalarda sırasıyla, yara iyileşmesi grubu vs. kontrol de 91 gen, rejeneratif grup vs. kontrol grubunda 351 gen, ve rejeneratif grup vs. yara iyileşmesi grubunda 280 gen istastiksel olarak kuvvetli anlamlı bulunmuştur (düzeltilmiş p değeri; p<0.01). Detaylı analizler, biyolojik gruplar arasında, her iki teknolojinin içinde ve arasında bulunan DE gösteren genler logaritmik kat değişiklikleriyle tutarlı bir korelasyon sergilemiştir. Gen ontolojisi analizleri, sonuçlarımızın aksolotl uzuv yara iyileşmesinde ve yenilenmesinde literatürle uyumlu olduğunu göstermiştir. Geliştirdiğimiz metadoloji aksolotl ekstremite rejenerasyonu üzerine yapılacak gelecek çalışmalara gelişmiş istatistiksel güç ve daha tutarlı sonuçlar için faydalı olabilecektir.

*Anahtar Sözcükler: aksolotl, yara iyileşmesi, rejenerasyon, birleşme, diferansiyel ifade.*

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# **Chapter 1**

# **Introduction**

The axolotl, *Ambystoma mexicanum*, is a tetrapod vertebrate which has been an imperative model system for the fields of developmental, evolutionary, and regenerative biology, due to its unique ability of reliably and fully regenerating various body parts, while most adult vertebrates lack such supremacy [1,2]. The Ambystomatidae*, Ambystoma tigrinum* complex, is a clade of 17 closely related, rapidly evolving species, living in an area spanning southern Canada to central Mexico, and having the axolotl as one of its recently derived members [2]. More specifically, the axolotl is a member of the Urodele amphibians, a group consisting of newts and salamanders that have similar vigorous regeneration capacities [1,3]. Axolotls are unique in their regenerative potential due to the fact that their juvenile features are preserved despite reaching sexual maturity [4]. Since they do not undergo metamorphosis naturally, they exhibit some embryonic-like cell traits [5] during adulthood, and thus, can regenerate their body parts efficiently throughout their whole life [1]. The organs which axolotls can faithfully regenerate are many, including their hearts [6–8], spinal cords [9], and even brain [10]. After induction of metamorphosis by thyroid hormone administration, decrease in regenerative power of this species is observed for some body parts such as limb [11,12], however based on recent studies

for other parts of the body regeneration capacity doesn't seem to be hindered [1,13]. Besides, unlike other vertebrates such as the amniotes, which have limited regenerative capacity, axolotls have a simpler adaptive immune system, suggesting that successive regeneration may require a weak inflammatory response [1,14].

Axolotl's regenerative capacity has been tested for many tissues. In response to partial ventricular amputation (PVA) in the heart of axolotl, proliferation of cardiomyocytes is initiated, and this is followed by restoration of the heart's functional capacity as well as the myocardium's structural recovery [6]. Factors such as Baf60 (BRG1/BRMassociated factor 60c), a component of ATP-dependent chromatic-remodeling complexes, has a central role in driving cardiomyocyte proliferation post-cardiac injury [7]. This process is also stimulated by an evolutionarily conserved response mediated by the activation of complement 5a receptor 1, suggesting a pivotal role of the complement pathway in promoting successful heart regeneration [8]. This animal is also capable of completely regenerating its injured or amputated spinal cord with cellular and functional accuracy [9]. When its tail is amputated, a unipolar injury is sensed and regeneration would proceed towards the tip. On the other hand, bipolar injuries resulting from transecting the spinal cord would initiate a diverse regenerative action; the caudal and rostral severed ends ultimately reconnect by bridging the gap. Acting as progenitor cells, ependymal cells expand themselves to form a neuroepithelial tube, thereby facilitating spinal cord regeneration [9]. The axolotl brain also has some regenerative potential, particularly when it comes to regenerating specific neural subtypes, however limited on the functional repair level [10]. It is able to regenerate molecularly-defined neuronal subtypes, while it fails to recover the axonal tracts circuitry that existed prior to injury, having settled in an altered tissue architecture, despite the electrophysiological functionality they seem to attain [10].

Another exceptional feature of axolotl is ability to regenerate its limbs. The phases and process that ensues from axolotl limb amputation can be described as follows: within around 24 hours post-amputation, a stump of epidermal cells migrates to the site of amputation forming a thin wound epidermis across the severed stump, which differs from intact, fully differentiated epidermis at the molecular and structural level [15,16].

This process is followed by infiltration of macrophages to the wound area to remove the pathogens from the wound zone and phagocyte the dead cells' debris within 48 hours post-amputation. Previous studies have demonstrated that macrophage activity is indispensable for successful regeneration [17]. Secretion of mitogens and growth factors from the epidermal cells is accompanied by innervation and, as a result, dedifferentiation of terminally differentiated cells and activation of progenitor cells by re-entering into the cell cycle are the key processes to form what's known as the blastema [16]. Blastema cells are characterized as highly proliferative, heterogeneous in origin and potential [18], morphologically resemble fibroblasts, exhibit unidirectional signaling that is influenced by wound epidermis factors, and behave as autonomous units [16]. Blastemas of a foot amputation and of a full leg amputation are fated to produce only a foot and a full leg, respectively, even when transplanted elsewhere [16]. Hence, blastemas are encoded with precise positional information. The blastema cells continue enriching their pool until reaching a definitive size, that's when they flatten out, allowing cartilage cells to merge and condense, and ultimately paving the way for the varied tissue types to be differentiated, ending up with a perfectly regenerated limb that is identical to the amputated one and finely sized regardless of the age or size of the animal [16].

Some important genes were shown to be directly implicated in axolotl wound healing and regenerative processes. For instance, fibroblast growth factors 8 (fgf8) and MARCKS-like protein were found enriched in early wound epidermis, and their function is proposed to be promoting cellular proliferation [19–22]. Further, heme oxygenase 1 (hmox1), matrix metalloproteinases 11, 1, 3, 9, 10 (mmp11, mmp1, mmp3, mmp9, mmp10), and tsp1 were proposed to function in the overall wound healing process [23–25]. Besides, fibroblast growth factor 10 (fgf10), msh homeobox 1 (msx1), msh homeobox 2 (msx2), and wingless-type MMTV integration site family members 5a and 5b (wnt5a, wnt5b) were found enriched in amputation wounds vs. lateral wounds [19,26–29]. As for genes involved in the regeneration, among the blastema-enriched genes are cold-inducible RNA-binding protein (cirbp) that was found to be cytoprotective for blastema cells, FUS RNA-binding protein (fus), heterogenous nuclear ribonucleoprotein A1 (hnRNP a1), growth-promoting kazal type

serine peptidase inhibitor domain 1 (kazald1), prothymosin alpha (ptma), retinolbinding protein 2a (rbp2a), and serine and arginine rich splicing factor (sfrs1) [25,30]. The tumor protein p53 was found to be downregulated during blastema formation and upregulated within 24 hpa over 2-3 days as well as during redifferentiation [25,31,32]. SMAD family member 2 (smad2) was found upregulated during late regeneration and is thought to be functioning in TGF-β1 signal transduction pathway [33].

Using Axolotl as a model organism is advantageous from several viewpoints. Their generation time is around 1 year or less and year-round breeding in the laboratory is not that difficult [16,34]. Several techniques such as transgenesis and genome editing have been implemented on these animals with relative success [35–39]. It is currently feasible to study mutant cells *in vivo* due to the development of localized genome editing [16]. Although the axolotl's genome is a simple diploid with 14 pairs of chromosomes, it's very large and highly repetitive, containing long introns [40]. Technical hurdles such as the inability of obtaining sufficient read-length and an improved assembly methodology have been some of the major obstacles towards having a full genome assembly [16], and only very recently sequencing and assembly of axolotl genome was reported [41]. Therefore, majority of studies aiming at unraveling the pathways and gene networks in the regenerative mechanisms in axolotl have utilized proteomic and transcriptomic tools [16,30,42–45]. By using the mRNA in the axolotl regenerative tissue as an experimental guide, techniques such as microarrays and transcriptomics (RNA-seq), along with the utilization of *de novo* assembled transcriptomes, have been the primary tools for studying the mechanisms of limb regeneration and discovering the identities of the involved transcripts [16].

Due to their standardization advantage, microarrays were an indispensable tool, capable of unlocking the identities of some of the genes driving the axolotl limb regeneration. Although downstream analyses cannot consider expressed genes that are not represented on the microarray, the technology can still be used to design probes for any condition of interest [16]. Similarly, gene discovery in axolotl limb regeneration was further fostered by the advancements in transcriptomics. RNA-seq is superior to microarrays in mainly two aspects; firstly, there is more dynamic range for expression values that could be detected by RNA-seq at a single-nucleotide resolution, and secondly, highly expressed genes can be accurately detected by their relative expression values with RNA-seq, eliminating the saturation effect that comes with using microarrays [16]. In addition, novel mRNA discovery for non-model systems as well as the ability to quantify isoforms of genes are other important features of RNA-Seq. Recent advances have made it possible to even use individual cells as the source of a very low RNA input, thereby drastically improving our knowledge on the specific cells and tissues involved in the limb regeneration [16,46].

Despite all of the aforementioned advancements in unraveling the mechanisms of axolotl limb regeneration by the use of microarrays and RNA-seq technologies, the axolotl literature is still missing a key methodology that has the potential in advancing the current knowledge on the limb regeneration even further. The various genes that have been identified to be implicated in the different stages of axolotl limb regeneration have been discovered by separate experiments from separate labs and with limited replicates. "Meta-analysis" is a key methodology widely used in many fields of science that mainly aims to provide scientific consensus on any particular research question [47]. The axolotl regeneration field could greatly benefit from this methodology due to the increasing amount of publicly available microarray and RNA-Seq data, along with freely available bioinformatic tools. One approach of doing so would be to improve candidate gene selection and establishing "biomarkers" for the axolotl wound healing process as well as the limb regenerative process, which is the core scope of this thesis. Meta-analysis is a commonly approach in biomedical sciences to detect differentiallyexpressed (DE) genes which may be further considered for selecting gene signatures or may be used as features for improving an existing classifier and coming up with a better gene signature for clinical applications [48–50].

The application of meta-analysis in many of the fundamental biological research as well as preclinical medical sciences has not been embraced very quickly due to the fact that experimental techniques may be a lot different for direct comparisons [47]. Besides, some data would be deposited with no relevant publication, making the analysis a lot more challenging. However, microarray and RNA-Seq data are being

deposited to public repositories along with their related publications and detailed experimental designs [47]. In addition, the advantages of implementing the metaanalysis methodology can be realized from the limitations of individual studies. First of all, the cost of utilizing new technologies is almost always considered a limiting factor when it comes to determining the scale of an experiment conducted by some lab. Moreover, after an individual experiment has been conducted, researchers are faced with challenging statistical issues [47]. Lastly but not least, in some cases experimental design of individual studies overlap with each other due to lack of an established pipeline to perform meta-analysis and as a consequence, researchers may generate similar data. These issues are manifested in both high false-positive observations due to the analysis of limited number of samples and huge number of transcripts, and falsenegative observations when false positives are accounted for by introducing stringent cut-offs [47,51]. Therefore, gene signature selection could be enhanced when multiple data sets are integrated by means of meta-analysis [47,50,52]. In other words, the more sample size increases, the more statistical power, the less individual study-specific biases, and the more precise differential gene expression integration and heterogeneity assessment can be achieved [50,53–56].

When the term "Meta-analysis" is used, it's often understood as the concept of integrative data analysis (IDA). However, conceptually, integrative data analysis has recently been expanded to refer to experiments which aim to integrate information from several layers of "omics" information (aka multi-omics), such as integration of epigenomics, genomics, transcriptomics, proteomics, and metabolomics [57]. In this thesis, we refer to IDA as the process of combining information of independent studies originating from different platforms or slight variations of the same platform [50,53]. Technically, there are two fundamental approaches to perform the latter concept of integrative data analysis; meta-analysis and cross-platform normalization (aka "merging") [50]. Meta-analysis is classified as "late stage" data integration when final statistics are combined from different studies, whereas merging is classified as "early stage" data integration when it integrates data before running the statistical test [50]. Relatively-homogenous datasets which have been selected to answer unambiguous, particularized questions can be used more suitably by the merging method for biomarker discovery [50,58]. Besides, both data integration methods are applicable under comparable conditions and for biological questions, whether it's differential expression analysis or class prediction [50].

In this thesis, integrative data analysis was independently performed on publicly available Microarray and RNA-Seq data from Axolotl samples, using the crossplatform normalization (merging) method to identify the genes which might be considered as biomarkers of different phases of regeneration. The samples were collected from different Microarray and RNA-Seq data sets, referring to three main groups of axolotl biological conditions; control (homeostasis), wound healing, and limb regeneration conditions. By separately using the merging methodology on the samples of Microarray and RNA-Seq technologies, followed by comparing their results, the aim was to identify a set of transcriptomic patterns that drive the wound healing and regenerative processes in the axolotl limb. The statistical test yielded 170, 1254, and 1047 differentially expressed (DE) genes (adjusted p-value < 0.01), commonly identified by Microarray and RNA-Seq integrative data analyses in wound healing vs. control, regenerative vs. control, and regenerative vs. wound healing comparisons, respectively. Moreover, the top 91 DE genes (commonly identified by the analyses of both technologies) in wound healing vs. control comparison enriched several biological processes (adjusted p-value  $< 0.05$ ) such as collagen metabolic processes, regulation of cell adhesion, proliferation, and death, as well as extracellular matrix disassembly. On the other hand, the top 351 DE genes (commonly identified by the analyses of both technologies) in regenerative vs. control comparison enriched several biological processes (adjusted p-value < 0.05) such as regulation of cell cycle processes, mitotic nuclear division, regulation of mRNA metabolic processes, muscle filament sliding and contraction, muscle structure development, and cardiac muscle tissue morphogenesis.

# **Chapter 2**

# **Methods**

## **2.1 Gene-expression Data Collection**

Gene-expression microarray data sets and RNA-seq data sets were collected from the public Gene Expression Omnibus (GEO) database [59,60] [\(http://www.ncbi.nlm.nih.gov/geo/\)](http://www.ncbi.nlm.nih.gov/geo/) and the European Nucleotide Archive (ENA) database [61] [\(https://www.ebi.ac.uk/ena\)](https://www.ebi.ac.uk/ena), respectively. The following criteria, prepared according to *Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)* [62]*,* were used to select GEO series from which data were collected (Figure 1 and Figure 2):

- 1) GEO series data deposited until September 2018.
- 2) Non-redundant series.
- 3) Series pertinent to Axolotl tissues.
- 4) Series having unduplicated datasets.

The accession number of the GEO series (GSE number), title, publication, number of the selected samples, number of the total samples, platform type, link to the geneexpression data, and the year of each study can be found in Table A.1 for Microarray technology and in Table A.2 for RNA-seq technology. The number of GSM files representing our meta-data design (group types), how many of each group belong to which sub-platforms and to which study (series), is provided in Table 1 for Microarray technology and in Table 2 for RNA-seq technology. For more detailed information on the GSM accession, timepoint, amputation/injury site, and replicate number of each sample, under each group type, for every selected GSE study, Table A.3 and Table A.4 were generated for Microarray and RNA-seq technologies, respectively.







**Figure 2**: Flow diagram illustrating the selection criteria used for performing integrative analysis on RNA-seq data. The diagram is prepared according to *Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)*



### **Table 1:** Summary of microarray gene expression data used for integrative analysis



**Table 2:** Summary of RNA-Seq gene expression data used for integrative analysis

## **2.2 Gene-expression Data Processing**

Gene-expression Microarray and RNA-seq integrative data analyses were performed using R software [67], software packages from the open development software Bioconductor Project [68,69], and parts of a published gene-expression analysis workflow [70].

The whole Microarray data processing workflow is provided in Figure B.1. The selected samples (CEL files) from the 3 Affymetrix datasets (GSE116615, GSE67118, GSE37198) were read and merged as a single dataset, due to their similarity at the probeset-level, using the R/Bioconductor "affy" package [71]. The resulting single dataset consists of 236 (21 control, 51 wound healing, 164 regenerative) samples (columns) and 20080 probesets (rows). This dataset was then summarized, quantilenormalized, and log2-transformed by applying the Robust Multichip Average (RMA) algorithm using the R/Bioconductor "affy" package [71]. Thereafter, the expression data underwent a filtering process based on row-wise transcript intensities. The medians of rows were calculated using the R/Bioconductor "Biobase" package [68], followed by keeping only the probesets with intensities higher than a threshold of "4" in at least as many samples of the smallest group (Figure 3A). The resulting filtered data consists of 17658 probesets. These probesets were then subjected to annotation using the AMBY\_002a520748F probeset annotation file  $\left(\sim 20k\right)$  provided by Sal-Site [\(http://www.ambystoma.org/genome-resources/20-gene-expression\)](http://www.ambystoma.org/genome-resources/20-gene-expression). There were 13316 probesets mapping to the annotation file with some of them mapping to the same gene. In order to obtain unique genes for those multiple mappings, using the "WGCNA" R package [72], the duplicated probesets were collapsed from probesetlevel to gene-level by taking the maximum row mean value of the probeset to represent the corresponding gene, resulting in a total of 10442 unique genes.

As for the Agilent dataset (GSE36451), the 77 selected samples (5 control, 42 wound healing, 30 regenerative) were obtained directly from GEO as summarized, quantilenormalized, and log2-transformed. The samples were combined together as a single

dataset having 77 samples (columns) and 43796 probesets (rows). The dataset underwent the same median intensity-based filtering as the Affymetrix datasets with the same threshold (Figure 3B), using the R/Bioconductor "Biobase" package [68]. This filtering resulted in 41579 probesets, which were further subjected to annotation using the annotation file obtained from GEO (https://www.ncbi.nlm.nih.gov/geo [/query/acc.cgi?acc=GPL15342\)](https://www.ncbi.nlm.nih.gov/geo%20/query/acc.cgi?acc=GPL15342). Only 21419 probesets were mapped to the annotation file, some of which corresponding to the same gene. Unique genes were obtained by the same approach used for the Affymetrix data, by collapsing the duplicated probesets to the corresponding genes, using the "maximum row mean values" method, implemented by the "WGCNA" R package [72], resulting in a total of 5083 unique genes.



**Figure 3:** Histograms of Median intensities. A) Histogram of the median intensities of the merged 3 Affymetrix datasets. B) Histogram of the median intensities of the Agilent dataset. The vertical red line represents the threshold such that all of the probeset median intensities below the threshold are discarded

In order to obtain a set of common genes between the Affymetrix and Agilent datasets, the 10442 Affymetrix unique genes were merged with the 5083 unique genes, resulting in 4322 unique common genes. The Affymetrix log2-transformed data was prepared based on the 4322 unique common genes, and so was the Agilent log2-transformed data. In order to minimize the batch effect between the Affymetrix and Agilent platforms, the resulting Affymetrix and Agilent log2-transformed data were each independently transformed to standard score (a.k.a "z-score") [73], which is performed by the process of centering (subtracting the column means of the transposed matrix from their corresponding columns) followed by scaling (dividing the centered columns of the transposed matrix by their standard deviations), and then transposing the matrix back so that genes are rows and samples are columns. The Affymetrix and Agilent z-scored data were merged together to obtain a single dataset consisting of 313 (26 control, 93 wound healing, 194 regenerative) samples (columns) and 4322 genes (rows). Principle component analysis (PCA) was implemented to explore overall relationship occurring among samples of the z-scored, merged data.

The whole RNA-seq data processing workflow is provided in Figure B.2. The selected raw data for each of the 5 datasets were obtained from the European Nucleotide Archive (ENA) in fastq format. GSE116777 (2 control, 3 wound healing), GSE92429 (3 control, 4 regenerative), and GSE103087 (4 regenerative) are all paired-end libraries, whereas both GSE74372 (1 control, 3 regenerative) and GSE34394 (1 control, 4 wound healing, 7 regenerative) are single-end libraries. Dwaraka *et al*., [63], recently produced the axolotl transcriptome "V5 contig assembly (contig length of 19,732 bp)" (data accessible at NCBI GEO database, accession GSE116777), and was downloaded to be used as our transcriptome reference. This particular transcriptome was chosen because, according to the authors, a total of 31,886 pairwise alignments with > 98% sequence similarity were identified between the V5 RNA-seq contigs and the 20,036 V3 contigs that were used to design the Affymetrix microarray probesets. Since the Affymetrix probesets already had an annotation file, and both were used in our microarray analysis pipeline, the same annotation file was used for generating a new annotation file for the 31,886 aligned contigs of the V5 assembly in our RNA-seq analysis pipeline. The RNA-seq annotation file was prepared by merging the 31,886

V5 assembly-V3 Affymetrix probesets alignment with the V3 Affymetrix probesets annotation file, yielding around 25k genes. The expression of transcripts of each of the 5 datasets were independently quantified using the transcriptome-wide quantifier "Salmon" tool [74], by building an index for the V5 transcriptome and directly quantifying the reads on it. Salmon operates on a dual-phase inference procedure, utilizes the concept of *quasi-mapping,* and accounts for technical biases by extensive bias modeling. These unique features enable salmon to carry out fast and accurate quantification of transcript abundance from RNA-Seq reads [74]. The resulting scaled counts generated from transcript abundances were imported along with the RNA-seq annotation file, using the R/Bioconductor "tximport" package [75]. This yielded a count matrix of the samples of all datasets combined (32 columns) with 10k unique genes (rows). Lowly expressed genes were filtered out using the R/Bioconductor "edgeR" package [76,77]. The filtering strategy is to keep genes that have minimum counts for at least some samples. The final format of the data post-filtering is a matrix with 32 (7 control, 7 wound healing, 18 regenerative) samples as columns and 7562 genes as rows. Normalization factors were calculated for this matrix using the R/Bioconductor "edgeR" package [76,77]. The normalization factors were used while converting the count data to log2-counts per million (logCPM), using the "voom" function of the R/Bioconductor "limma" package [78–80], which makes the data ready for linear modelling for differential expression analysis. When applying the "voom" function, a design matrix was implemented such that each sample's group type and study origin are accounted for. In order to explore overall relationship occurring among samples, principle component analysis (PCA) was performed on the "voom" counts data.

### **2.3 Differential Expression Analysis (DEA)**

Microarray DEA was performed on the z-scored, combined data (313 samples, 4322 genes). RNA-seq DEA was performed on the logCPM (voom) counts (32 samples, 7562 genes). The following analyses were performed using the R/Bioconductor "limma" package [78–80].

For both Microarray and RNA-seq data, contrast matrices were constructed to represent 3 group comparisons; wound healing vs. control, regenerative vs. control, and regenerative vs. wound healing. The first comparison aims to observe gene expression changes occurring in wound healing tissues compared to control (homeostatic) tissues. The second comparison aims to observe gene expression changes occurring in regenerative tissues compared to control (homeostatic) tissues. The final comparison aims to observe gene expression changes occurring in regenerative tissues compared to wound healing tissues. For each contrast matrix, a design matrix was incorporated to account for the group type and study origin of every sample, and a linear model is fitted to the expression data for each gene. Empirical Bayes method was applied on those fitted linear models, so that genes can be ranked based on an order of evident differential expression. The raw p-value and adjusted p-value distribution for each contrast from both Microarray and RNA-seq data were plotted in a histogram format as a diagnostic check. The adjusted p-value method used here is the Benjamini-Hochberg (BH) that controls the expected false discovery rate (FDR) below a specified value. The cutoff for adjusted p-value was set to be 0.01, so genes with lower adjusted p-values were extracted as lists of differentially expressed genes, each list corresponding to each contrast of either the Microarray or RNA-seq data. In order to explore how differentially expressed genes drive the clustering of the samples, principal component analysis was performed for each of the 3 comparisons, for both the Microarray z-scored data as well as the RNA-seq logCPM counts data, with the batch effect minimized using the R/Bioconductor "limma" package. The comparison of DE Genes among the three comparisons within each technology, and the subsequent comparison of the DE genes between the two technologies (Microarray and RNA-seq), were performed using Venn diagram online tool [\(http://bioinformatics.psb.ugent.be/webtools/Venn/\)](http://bioinformatics.psb.ugent.be/webtools/Venn/) and scatter plots using the R/Bioconductor "ggplot2" package [81]. Pair-wise correlation testing of logFC of the DE genes for the three comparisons within and between the two technologies was performed using the "Spearman" correlation test in base R.

## **2.4 Gene Ontology Enrichment Analysis**

The top DE genes commonly identified by both technologies analyses were used to identify Gene Ontology (GO) annotations using the R/Bioconductor "clusterProfiler" package [82] . The genes were first converted to Entrez IDs prior to performing the statistical overrepresentation test, which was used to separately query the top upregulated and down-regulated Entrez ID-mapped genes of each condition comparison against all GO lists (Biological Processes "BP", Cellular Components "CC", Molecular Functions "MF"), while also eliminating redundant GO terms. The background gene list consisted of all Entrez IDs from the axolotl Affymetrix "AMBY\_002a520748F" annotation file. Bar plots were used to visualize the top 20 GO terms enriched by the up-regulated and down-regulated genes for the conditions of interest. The parameters of the overrepresentation test included using the homo sapiens "org.Hs.eg.db" as the organism database, Benjamini & Hochberg (BH) as the adjusted-P value method, and setting p and q value cut-offs to 0.05.

# **Chapter 3**

## **Results**

### **3.1 Gene-expression Data Selection and Search Criteria**

According to our criteria, illustrated in Figure 1 for Microarray technology, 4 GSE datasets (series) were selected, 3 of which were performed using slightly different versions of the Affymetrix Ambystoma Mexicanum platform; the version used by GSE116615 is GPL25286 [AMBY\_002a520748F], while the version used by both GSE67118 and GSE37198 is GPL15153 [AMBY\_002a520748F]. The fourth study, GSE36451, was carried out using the Agilent-019788 Ambystoma Mexicanum platform with version GPL15342 [44k\_v3\_20080327]. Tables A.1 and A.3 provide detailed information on the selected studies' overall design, number of total and selected samples, and the group types we designed. The groups were categorized into three types; "control" group (intact/amputated/injured limbs and/or flank wounds at 0 hour time points), "wound healing" group (intact/amputated/injured limbs and/or flank wounds up until around 50-hour time points), and "regenerative" group (intact/amputated/injured limbs and/or flank wounds of time points later than around 50 hours to 28dpa). From these datasets, samples that are denervated limbs (in GSE37198) which don't aid in regeneration, or limb buds (in GSE36451) which are distinct from a fully mature amputated limb, were excluded. Totally, 6 samples from

GSE116615 dataset, 198 samples from GSE67118 dataset, 32 samples from GSE37198 dataset, and 77 samples from GSE36451 dataset were selected, forming a total of 313 samples to be analyzed. From these, 26 samples belong to the control group, 93 samples belong to the wound healing group, and 194 belong to the regenerative group (Table 1).

As for the criteria for RNA-seq technology, illustrated in Figure 2, 5 GSE datasets (series) were selected, all of which were performed using slightly different versions of the Illumina Ambystoma Mexicanum platform. The version used by GSE116777 is GPL21473 HiSeq 2000, while the version used by both GSE103087 and GSE92429 is GPL22800 HiSeq 2500, and the version used by both GSE74372 and GSE34394 is GPL14997 Genome Analyzer IIx. Tables A.2 and A.4 provide detailed information on the selected studies'overall design, number of total and selected samples, and the group types we designed. Three group types (control, wound healing, regenerative) were assigned similarly to that of the aforementioned Microarray groups categorization. From GSE116777 dataset, one sample was excluded due to it being an outlier, as identified by the authors [63]. From GSE103087, 4 samples were excluded because they underwent many rounds of amputation-regeneration. From GSE74372, 4 samples were small RNA (sRNA) profiling expression experiments, and so they were excluded. From GSE34394, 8 samples were excluded for being mouse samples. In the last dataset, GSE92429, there are many samples coming from various positions along the axolotl limb, among others, and so the upper-arm samples were selected as part of the control group in order to be as consistent as possible with the other samples from other datasets regarding the investigated site. Two other sample types from the latter dataset, distal and proximal, being the blastemal stage of the regenerating limb, were selected and all other samples were excluded. Totally, 5 samples from GSE116777 dataset, 4 samples from GSE103087 dataset, 7 samples from GSE92429 dataset, 4 samples from GSE74372 dataset, and 12 samples from GSE34394 dataset were selected, forming a total of 32 samples to be analyzed. From these, 7 samples belong to the control group,

7 samples belong to the wound healing group, and 18 belong to the regenerative group (Table 2).

## **3.2 Whole Gene Expression Data-based Principal Component Analysis**

The principal component analysis performed on the z-scored, combined Microarray data having 4322 genes (Figure 4) shows that the first principal component (PC1) roughly separates between the samples based on their group types. This suggests that the source of variation is likely due to differential expression between the group types. The second principal component (PC2), however, separates the samples based on their study origin.

On the other hand, the principal component analysis performed on the voom-counts RNA-seq data having 7562 genes (Figure 5) shows that the first principal component tends to separate the samples based on their study origin, conspicuously between the GSE34394 and the rest. However, the second principal component seems to roughly separate the samples based on their group types. Overall, regarding this whole gene expression data-based principle component analysis approach, it seems that batch factor (study origin) is more important than the time points (group types) to separate the samples in both Microarray and RNA-seq data.



**Figure 4:** Principal component analysis for the Microarray quantile-normalized, log2 transformed, z-scored, combined data having 4322 genes**.** A) Control and Wound Healing. B) Control and Regenerative. C) Wound healing and Regenerative. The number of samples per group are: 26 Control, 93 Wound healing, and 194 Regenerative.



**Figure 5:** Principal component analysis for the RNA-seq logCPM (voom) counts, having 7562 genes. A) Control and Wound Healing. B) Control and Regenerative. C) Wound healing and Regenerative. The number of samples per group are: 7 Control, 7 Wound healing, and 18 Regenerative.

## **3.3 Distribution of Raw and Adjusted P-values**

For both Microarray (Figure 6) and RNA-seq (Figure 7) DEA results, for every comparison, p-value and adjusted p-value histograms were plotted. Corresponding to true null hypotheses, a uniform distribution for the p-values is expected, with low pvalues enrichment corresponding to differentially expressed genes at the near-zero peak. In line with the expectations, p-values of every comparisons from both microarray and RNA-Seq analyses show enrichment near-zero peak corresponding to differentially expressed genes.



**Figure 6**: P and adjusted-P value distribution (microarray). p-value histogram (left) and adj.P.Value histogram (right) after DEA on Microarray data for the following comparisons A,B) wound healing vs. control, C,D) regenerative vs. control,E,F) regenerative vs. wound healing.



**Figure 7**: P and adjusted P-value distribution (RNA-Seq). p-value histogram (left) and adj.P.Value histogram (right) after DEA on RNA-seq data for the following comparisons A,B) wound healing vs. control, C,D) regenerative vs. control,E,F) regenerative vs. wound healing.
#### **3.4 DEA-based Principal Component Analysis**

The principal component analysis performed on the z-scored, combined Microarray data for the differentially expressed genes of each of the three comparisons (Figure 8) shows that the first principal component (PC1) clearly separates the samples based on their group types. This verifies that the source of variation is due to differential expression between the group types. The second principal component (PC2), however, doesn't seem to strongly indicate any particular type of separation. Wound healing vs. control comparison had 2092 DE genes (adj p-value  $< 0.01$ ), while regenerative vs. control and regenerative vs. wound healing comparisons had 2748 and 3166 DE genes (adj p-value  $< 0.01$ ), respectively.

On the other hand, the principal component analysis performed on the voom-counts RNA-seq data for the differentially expressed genes of each of three comparisons (Figure 9) shows that, unlike the whole gene expression data-based PCA, the first principal component (PC1) clearly separates the samples based on their group types, while the second principal component (PC2) seemingly indicate no specific separation of any type. Therefore, the high variation and separation that PC1 illustrates, proves that differential expression between group types is the dominant source of variation. The DEA-based PCA performed on both Microarray and RNA-seq data indicate a successful minimization of the batch effect among studies, making the observation that group types are separated due to differential expression the dominant one. Wound healing vs. control comparison had  $423$  DE genes (adj p-value  $< 0.01$ ), while regenerative vs. control and regenerative vs. wound healing comparisons had 2992 and 2371 DE genes (adj p-value  $< 0.01$ ), respectively.



**Figure 8**: Principal component analysis for the Microarray quantile-normalized, log2 transformed, z-scored, combined data after DEA**.** A) wound healing vs. control (2092 DE genes, 119 samples)**.** B) regenerative vs. control (2748 DE genes, 220 samples). C) regenerative vs. wound healing (3166 DE genes, 287 samples). The number of samples per group are: 26 Control, 93 Wound healing, and 194 Regenerative. The DE genes have an adjusted p-value  $< 0.01$ .



**Figure 9:** Principal component analysis for the RNA-seq logCPM (voom) counts, after DEA**.** A) wound healing vs. control (423 DE genes, 14 samples)**.** B) regenerative vs. control (2992 DE genes, 25 samples). C) regenerative vs. wound healing (2371 DE genes, 25 samples). The number of samples per group are: 7 Control, 7 Wound healing, and 18 Regenerative. The DE genes have an adjusted p-value < 0.01.

#### **3.5 Distribution of Differentially Expressed Genes**

DE genes from Microarray data were found to be distributed among the three comparisons. I.e. genes may be differentially expressed in one, two, or all of the comparisons (Figure 10).



**Figure 10**: Venn Diagram of the distribution of significantly DE genes (adj.p  $\leq 0.01$ ) among the three comparisons, from Microarray data; Wound healing (Wh) vs. Control (Ctrl), Regenerative (Reg) vs. Control (Ctrl), and Regenerative (Reg) vs. Wound healing (Wh). Each complete circle represents the number of differentially expressed genes of a certain condition comparison as resulted by DEA.

There are 42 genes uniquely DE in wound healing vs. control comparison, 105 genes uniquely DE in regenerative vs. control comparison, and 405 genes uniquely DE in regenerative vs. wound healing comparison. There are 457 genes commonly DE in regenerative vs. control and wound healing vs. control comparisons, 1168 genes commonly DE in regenerative vs. control and regenerative vs. wound healing comparisons, 575 genes commonly DE in wound healing vs. control and regenerative vs. wound healing comparisons, and 1018 genes commonly DE in all three comparisons. Those genes commonly DE among comparisons, however, may not necessarily share the same gene regulation status, i.e., a gene may be up-regulated in one comparison and down-regulated in another comparison. To test this notion, the correlation of the logFC of the genes common in two or more comparisons was calculated in a pair-wise manner and scatter plots were plotted to visualize the differential expression pattern for each gene.

The Spearman correlation coefficients for the logFC of the genes commonly DE in regenerative vs. control and regenerative vs. wound healing comparisons (Figure 11A) as well as in regenerative vs. control and wound healing vs. control comparisons (Figure 11C) are 0.85 and 0.96, respectively.

The positive correlation indicates that the DE genes common in those condition comparisons are mostly regulated in the same direction; meaning that they are mostly either up-regulated or down-regulated at the two different condition comparisons sharing those DE genes. However, the logFC of the 575 genes commonly DE in wound healing vs. control and regenerative vs. wound healing comparisons show a negative correlation, having a Spearman correlation coefficient of  $-0.71$ , indicating that those genes are mostly oppositely regulated in these two different condition comparisons, i.e., most of those 575 genes are up-regulated in one of the two comparisons and downregulated in the other comparison (Figure 11B).

The pair-wise correlation testing for the 1018 genes DE in all three comparisons shows that the genes shared by all three comparisons follow the same trend as when they are shared by only the two corresponding comparisons (Figure 11D-F), having a positive correlation for regenerative vs. control and regenerative vs. wound healing comparisons (0.52 Spearman correlation coefficient) and for regenerative vs. control and wound healing vs. control comparisons (0.77 Spearman correlation coefficient),

and a negative correlation, though very low magnitude, for regenerative vs. wound healing and wound healing vs. control  $(-0.02$  Spearman correlation coefficient).



**Figure 11**: Scatter plot of the log-fold change of significant genes (adj.p <0.01) shared by two or more comparisons as shown in the Venn diagram (Figure 10), from Microarray data. A) Scatter plot of the logFC of the 1168 DE genes shared by Regenerative vs. Control and Regenerative vs. Wound healing comparisons. B) Scatter plot of the logFC of the 575 DE genes shared by Regenerative vs. Wound healing and Wound healing vs. Control comparisons. C) Scatter plot of the logFC of the 457 DE genes shared by Regenerative vs. Control and Wound healing vs. Control comparisons. D-F) Pair-wise scatter plots of the logFC of the 1018 DE genes shared by all three comparisons; D) Regenerative vs. Control and Regenerative vs. Wound healing, E) Regenerative vs. Control and Wound healing vs. Control, F) Regenerative vs. Wound healing and Wound healing vs. Control.

Additionally, DE genes from RNA-seq data were also found to be distributed among the three comparisons (Figure 12). There are 62 genes uniquely DE in wound healing vs. control comparison, 1226 genes uniquely DE in regenerative vs. control comparison, and 573 genes uniquely DE in regenerative vs. wound healing

comparison. There are 145 genes commonly DE in regenerative vs. control and wound healing vs. control comparisons, 1582 genes commonly DE in regenerative vs. control and regenerative vs. wound healing comparisons, 177 genes commonly DE in wound healing vs. control and regenerative vs. wound healing comparisons, and 39 genes commonly DE in all three comparisons.



**Figure 12:** Venn Diagram of the distribution of significant genes (adj.p <0.01) among the three comparisons, from RNA-seq data; Woun -healing (Wh) vs. Control (Ctrl), Regenerative (Reg) vs. Control (Ctrl), and Regenerative (Reg) vs. Wound healing (Wh). Each complete circle represents the number of differentially expressed genes of a certain condition comparison as resulted by DEA.

The correlation of the logFC of the genes common in two or more comparisons was also calculated in a pair-wise manner, and interestingly, the same pattern of gene regulation directionality occurred as with those from Microarray data.

The Spearman correlation coefficients for the logFC of the genes commonly DE in regenerative vs. control and regenerative vs. wound healing comparisons (Figure 13A) as well as in regenerative vs. control and wound healing vs. control comparisons (Figure 13C) are 0.94 and 0.93, respectively.

The positive correlation, therefore, indicates that genes commonly DE in those condition comparisons are mostly either up-regulated or down-regulated. On the other hand, the logFC of the 177 genes commonly DE in wound healing vs. control and regenerative vs. wound healing comparisons have a negative correlation (-0.95 Spearman correlation coefficient), indicating that those genes are mostly up-regulated in one of the two different condition comparisons and down-regulated in the other (Figure 13B).

The 39 genes DE in all three comparisons follow the same gene regulation trend as when they are shared by only the two corresponding comparisons, as shown by pairwise correlation testing of those genes (Figure 13D-F).



**Figure 13**: Scatter plot of the log-fold change of significant genes (adj.p  $\leq 0.01$ ) shared by two or more comparisons as shown in the Venn diagram (Figure 12), from RNA-seq data. A) Scatter plot of the logFC of the 1582 DE genes shared by Regenerative vs. Control and Regenerative vs. Wound healing comparisons. B) Scatter plot of the logFC of the 177 DE genes shared by Regenerative vs. Wound healing and Wound-healing vs. Control comparisons. C) Scatter plot of the logFC of the 145 DE genes shared by Regenerative vs. Control and Wound healing vs. Control comparisons. D-F) Pair-wise scatter plots of the logFC of the 39 DE genes shared by all three comparisons; D) Regenerative vs. Control and Regenerative vs. Wound healing, E) Regenerative vs. Control and Wound healing vs. Control, F) Regenerative vs. Wound healing and Wound healing vs. Control.

The correlation for regenerative vs. control and regenerative vs. wound healing comparisons (0.03 Spearman correlation coefficient) and for regenerative vs. control and wound healing vs. control comparisons (0.54 Spearman correlation coefficient) is positive, and for regenerative vs. wound healing and wound healing vs. control is negative (-0.71 Spearman correlation coefficient).

#### **3.6 Comparison of DE Genes Identified Based on Microarray and RNA-Seq Data**

The number of genes used for DEA from Microarray and RNA-seq data was 4322 and 7562, respectively. Because these genes share the same annotation source (AMBY\_002a520748F probeset annotation file), there are 3653 genes common between the two technologies (Figure 14).



**Figure 14**: Venn Diagram of the initial number of genes used before differential expression analysis. This number for each platform is obtained just after the filtering and /or merging.

Therefore, there will naturally be varying number of common DE genes per condition comparison between the technologies. By merging the DE lists (adj p-value  $< 0.01$ ) of both technologies together for each comparison, we found that 170, 1254, and 1047 genes that are DE in wound healing vs. control, regenerative vs. control, and regenerative vs. wound healing comparisons, respectively, are from both technologies (Figure 15A,C,E). The correlation of the logFC of the DE genes common between the technologies for each comparison was calculated and visualized by scatter plots. The

logFC of the 170, 1254, and 1047 genes identified as DE from both technologies in wound healing vs. control, regenerative vs. control, and regenerative vs. wound healing comparisons all have a positive correlation, with a Spearman correlation coefficient of 0.74, 0.71, and 0.77, respectively (Figure 15B,D,F).



**Figure 15**: Venn diagrams of the distribution of DE genes (adj p-value < 0.01) between Microarray and RNA-seq data as well as scatter plots of the log-fold change of the common DE genes between the two technologies for A,B) wound healing vs. control, C,D) regenerative vs. control, and E,F) regenerative vs. wound healing

Although our lists of DE genes commonly identified by both technologies are significant (adjusted p-value  $< 0.01$ ) for each condition comparison, there are many genes that have very low logarithmic fold change ( $logFC$  magnitudes  $< 1$ ). Therefore, a more reliable attribution of "DE" genes would be to extract the top significant genes, by a criterion, from the list of DE genes commonly identified by both technologies. Even though the correlation coefficients of the DE genes between technologies for each comparison was positive with fairly high magnitude, an added benefit to extracting top DE genes would be to further decrease the number of genes with conflicting gene

expression directionality between technologies for each condition comparison. So, the criterion for extracting the top DE genes is as follows: first, genes with logFC magnitudes  $> 1$  are extracted from both Microarray and RNA-Seq DE lists, independently. Then, the resulting two lists are merged together, yielding the top DE genes identified from both microarray and RNA-Seq. Consequently, the extracted top DE genes commonly identified by the two technologies are 91 genes in wound healing vs. control, 351 genes in regenerative vs. control, and 280 genes in regenerative vs. wound healing comparisons. The list of these genes along with their logFC from both technologies is provided in Table A.5. The correlation of the logFC of those top DE genes common between the technologies was also calculated and visualized by scatter plots. The logFC of the 91, 351, and 280 genes identified as the top DE genes from both technologies in wound healing vs. control, regenerative vs. control, and regenerative vs. wound healing comparisons all have an overall positive correlation, with a Spearman correlation coefficient of 0.44, 0.72, and 0.76, respectively (Figure 16).



**Figure 16**: Scatter plots of the log-fold change of the top DE genes (adj p-value  $< 0.01$ ,  $logFC$  magnitudes  $> 1$ ) commonly identified by Microarray and RNA-seq technologies for A) wound healing vs. control (91 top DE genes), B) regenerative vs. control (351 top DE genes), and C) regenerative vs. wound healing (280 top DE genes).

#### **3.7 Gene Ontology Enrichment Analysis of the Top DE Genes**

By using the overrepresentation test, several different gene ontology terms of biological processes, cellular components, and molecular functions were reported to be enriched by the top DE genes commonly identified by both technologies' analyses, for the condition comparisons. The top 86 up-regulated and 4 down-regulated genes in wound healing vs. control comparison enriched 80 GO terms and 2 MF terms, respectively (Table A.6). Among the top biological processes enriched by the top 86 up-regulated genes in the latter comparison are found as: positive regulation of cell death, cytokine-mediated signaling pathway, collagen metabolic process, negative regulation of cell adhesion, positive regulation of cell proliferation, and regulation of cell migration (Figure 17A). The top 181 up-regulated and 166 down-regulated genes in regenerative vs. control comparison enriched 64 and 142 GO terms, respectively (Table A.7). Mitotic nuclear division, chromosome segregation, mitotic spindle organization, RNA splicing, regulation of cell cycle process, and regulation of mRNA metabolic process were seen as the top biological processes enriched by the top 181 up-regulated genes in the latter comparison (Figure 17B). On the other hand, muscle filament sliding, muscle contraction, heart contraction, generation of precursor metabolites and energy, regulation of muscle contraction, and muscle structure development were recognized as the top biological process enriched by the top 166 down-regulated genes in the latter comparison (Figure 17C). A total of 128 and 109 GO terms were enriched by the top 150 up-regulated and 128 down-regulated genes in regenerative vs. wound healing comparison (Table A.8).



**Figure 17:** Bar plots showing the top 20 GO biological processes with their corresponding enriched gene counts. The bars are colored according to the adjusted p-value of the corresponding process. A) Top 20 GO processes for the top upregulated genes in wound Healing vs. control comparison. B) Top 20 GO processes for the top upregulated genes in regenerative vs. control comparison. C) Top 20 GO processes for the top downregulated genes in regenerative vs. control comparison. The genes used for the GO enrichment analysis are the top DE genes commonly identified by Microarray and RNA-seq analyses.

### **Chapter 4**

# **Discussion**

In this thesis, integrative data analysis was performed on axolotl gene-expression data. To the best of our current knowledge, this is the first study describing the investigation of differentially expressed genes implicated in the wound healing and regenerative mechanisms of the axolotl limb by integrative analysis of publicly available Microarray and RNA-Seq data.

Although the technical "meta-analysis" (late-stage data integration) method of integrative data analysis has more frequently been used in the literature compared to the early-stage data integration (merging) method [50], the latter method has been applied in multiple studies [50,83–85] and was particularly chosen for the aim of our study. It has been proposed that late-stage data integration performs worse that the direct-merging approach when the purpose is to identify robust biomarkers [50]. In other words, "deriving separate statistics and then averaging is often less powerful than directly computing statistics from aggregated data" [50,86]. For example, crossplatform normalization (early-stage data merging) yielded more differentiallyexpressed genes than meta-analysis as reported by Taminau *et al*. [53]. Furthermore, when prediction models are applied to a subset of studies, the data merging method can

facilitate the application of these models onto different studies from different platforms [48,50].

While samples from different datasets across different platforms are considered as a single dataset by the "data merging" method for testing the same hypothesis, systematic biases are a common issue [50,53,58,87], wherein they introduce undesirable nonbiological differences (batch effects) in the downstream gene signature analysis which can mask the real biological differences among the conditions of interest. Many different intra-laboratory variables are not clearly specified by some labs when their datasets are deposited into GEO and, because of that, we had to presume the uniformity of such variables across different datasets. For example, amputation site, size, feeding, and maintenance protocols of Axolotls are among those factors that can influence the clustering among the investigated samples, especially if a limited number of samples is being analyzed. This could lead to some difficulty in the interpretation of whether samples are inherently different due to gene-expression differences between particular amputation timepoints or due to other kinds of factors which were unaccounted for during the data selection and processing. Therefore, those factors could play a critical role in interpreting the whole gene expression data-based PCA for each condition comparison (Figures 4 and 5). Nevertheless, since one of the major aims of this thesis was to increase sample size as much as possible for gaining more statistical power, those presumed biological variations can be neglected, provided that real biological differences among group types can be clearly observed following differential geneexpression analysis. Indeed, DEA-based PCA showed a clear separation between experimental groups indicating an indecisive role of those presumed factors (Figures 8 and 9). Importantly, the application of transformation and normalization techniques during the process of data merging [50,73] along with accounting for the experiment source (study origin) for each sample while applying DEA using the limma method [78], were the major approaches for minimizing the observation of batch effects and maximizing the observation of gene-expression differences between experiment groups.

The validity and accuracy of conducting DEA on the Microarray and RNA-Seq data can be realized from the consistency of the results obtained from each technology with one another. Firstly, as the Spearman coefficients indicate, every pair-wise distribution of the DE genes among the three condition comparisons from Microarray data (Figures 10 and 11) are consistent with those from RNA-Seq data (Figures 12 and 13). The genes that are commonly DE in regenerative vs. control and regenerative vs. wound healing comparisons always have a positive correlation (Figures 11A,D and 13A,D), as do those genes commonly DE in regenerative vs. control and wound healing vs. control comparisons (Figures 11B,E and 13B,E). Also, the genes that are commonly DE in regenerative vs. wound healing and wound healing vs. control comparisons always have a negative correlation (Figures 11C,F and 13C,F). These consistent correlations also strongly suggest a true biological behavior of those DE genes across the conditions. Secondly, the Spearman correlation coefficients show that the DE genes as well as the top DE genes commonly identified by both Microarray and RNA-Seq data analyses are positively correlated with fairly strong magnitude for each of the three condition comparisons (Figures 15 and 16). Such strong positive correlations between microarray and RNA-Seq data was found in several previous studies [88–91]. Despite having such a positive correlation for most of the DE genes, some genes have opposing gene expression directionality. This might be due to the artifacts of gene expression technologies. However, the number of those genes with opposite direction was found significantly low for the top DE genes (Figure 16). The lower Spearman coefficient which was observed for the top DE genes in wound healing vs. control  $(r_s = 44)$ , despite having only a single inversely correlated gene out of 91, could be attributed to the difference between the logFC range of the DE genes from microarray data and those of RNA-Seq data. Consequently, the strength of the logFC magnitude for some genes might significantly differ, and thus, the whole pair-wise correlation would similarly be affected.

In response to limb amputation, the typical wound healing process is characterized by the induction of stress signals and damage-associated molecules [92]. During the first 6-8 hpa, epithelial cells migrate to and cover the amputation site [93], forming the "wound epithelium (WE)" beneath which are extracellular and cellular debris along with a damaged vasculature [64]. We found thbs1 as the top up-regulated gene in wound healing vs. control comparison, which is specifically highly up-regulated in basal cells of the wound epidermis that lacks a basement membrane at 24 hpa [63,94]. We also found that metalloproteinases (mmp1, mmp3, mmp19) along with their regulator timp1 [63], which are important to regulate the extracellular matrix and enriched in the wound epidermis immediately after injury [95], to be amongst the top up-regulated wound healing vs. control genes, as were extracellular matrix-generating components such as tnc [63]. At the wound healing phase, innate immunity elements; neutrophils, macrophages, and granulocytes are infiltrated into the regenerating limb at around 24 hpa [17]. Our wound healing vs. control top up-regulated genes also enriched several immunological processes, such as tissue histolysis (mmp1, mmp3, mmp19, timp1), inflammation (ptgs2), and host-defense molecules at the site of injury (zyx, mpo, cybb) [63]. In addition to innate immunity components, some biomarkers of leukocytes (lgals9, mpo) were also up-regulated [63]. In response to leukocytes infiltration, chemokines are expected to be released [63], and our results confirmed that some of genes (arg1, bcl2l1, cxcr4, egr1, hmox1, junb, lmnb1, mmp1, mmp2, mmp3, peli1, ptgs2, socs1, sqstm1, timp1, ywhaz) were up-regulated in wound healing vs. control data and these genes were enriched in cytokine-mediated signaling pathway GO term. Many of those genes enriched a variety of other GO terms associated with tissue development, cell death, proliferation, migration, and immune responses, which is probably due to the fact that most of those processes are activated by the cytokine signaling pathway [63].

It's been previously shown that when the regeneration phase starts at 2 dpa onwards, genes that are up-regulated within this interval enrich terms associated with DNA replication, mitosis, and the cell cycle [25]. The majority of these genes are upregulated during the 2-3 dpa interval, marking a transition phase in the limb regeneration program, after which they either gradually increase or sustain a relatively constant expression until the 28 dpa period [25]. We similarly found that the regenerative vs. control top up-regulated genes enriched many cell cycle related GO terms, such as positive regulation of cell cycle (apex1, aurka, aurkb, ccnj, fen1, hcfc1, kif23, mad2l1, mtbp, nipbl, pggt1b, rps6kb1, sfpq), mitotic nuclear division (aurka,

aurkb, ccnj, cdc20, cdca8, flna, kif11, kif22, kif23, mad2l1, mad2l1bp, mtbp, nek2, nipbl, plk1, prc1, rcc1, trip13), and DNA conformation change (asf1b, hells, hist3h2bb, hmgb2, nasp, nipbl, rpa2, sart3, top1, top2b). This indicates that the distal limb stump undergoes a remarkable change in the population of proliferative cells due the punctuated increase in the transcripts associated with cell cycle processes [25].

The expression of muscle-specific genes has previously been reported to be significantly reduced during limb regeneration [24,25,63,66,96]. Although muscle tissue remodeling is observed in the limb stump along with reduced muscle-specific transcripts during early response to limb amputation [63], by around 10 dpa the expression of those muscle-specific genes significantly drops, implying absence of muscle tissues [25]. It's been propounded that for progenitor cells to be recruited and for blastemal outgrowth to be initiated, muscle tissue depletion is necessary in the blastemal area [63]. Indeed, our top down-regulated regenerative vs. control genes enriched many muscle tissue-specific GO terms, including muscle filament sliding  $(\text{actal}, \text{actcl}, \text{actn3}, \text{des}, \text{mybpc2}, \text{mybpc3}, \text{myh2}, \text{myh4}, \text{myh7}, \text{myl1}, \text{myl2}, \text{myl3}, \text{myl$ myl4, tnnc1, tnnc2, tnni1, tnni2, tnnt1, tnnt3, tpm1, tpm3), regulation of muscle contraction (abat, actn3, anxa6, bin1, mybpc3, myh7, myl2, myl3, tnnc1, tnnc2, tnni1, tnni2, tnnt1, tnnt3, tpm1), and muscle cell development (acta1, actc1, bin1, mybpc2, mybpc3, myh10, myl2, myoz1, tnnt1, tnnt3, tpm1). In addition, it was previously documented that the regenerative phase, especially around 10 dpa, undergoes reduction in metabolic processes-associated transcripts [25,63]. Among the top down-regulated regenerative vs. control genes, we also found some genes that enriched a variety of cellular metabolic GO processes such as NADH metabolic process (actn3, gapdh, gpd1, gpi, mdh2, pfkm, pgk1, slc25a12, tpi1), ATP biosynthetic process (actn3, gapdh, gpd1, gpi, pfkm, pgk1, pgm1, prkag2, slc25a12, tpi1), and regulation of ATPase activity (atp1b2, gabarapl2, mybpc3, myl3, myl4, tnnc1, tnnt3, tpm1). It's been also shown that, although muscle-specific genes are significantly down-regulated over the regenerative phase, some of the metabolic genes do not drop in such an absolute manner, but instead they moderately drop during the regenerative phase [63]. It is suggested that, unlike the cells that die or undergo reprogramming, some other cells make up for the lost cellular metabolic genes, and thus, this moderate and incomplete metabolic gene expression is observed [63]. Likewise, we did observe this kind of relationship between the muscle-specific genes (myh6, myh3, mybpc3, myl1, myl2, myl3, tpm1), most of which are among the top down-regulated regenerative vs. control genes, and some of the metabolic genes that function in the electron transport chain and locate to mitochondria (dld, ndufb9, ndufc2, ndufs7, ndufv2, slc25a12, uqcrc2, uqcrfs1), most of which are not among the top DE genes, but rather among the downregulated regenerative vs. control genes. However, all of those metabolic genes are much less down-regulated than the muscle-specific genes over the regenerative phase. Notably, when our "top DE genes" is discussed, it's referring to those top DE genes commonly identified by the analyses of both Microarray and RNA-Seq. However, two of the aforementioned muscle-specific genes (myh6, myh3) and the metabolic gene (ndufv2) are actually found DE (adj p-value  $< 0.01$ ) only in RNA-Seq DEA. In fact, those 3 genes were never part of the 4322-microarray gene list that was used for Microarray DEA. This is important to show that the reliability of our results may be extended to those DE genes identified specifically by RNA-Seq DEA, and not to be limited to those DE gene commonly identified by both technologies, because many genes that were used for RNA-Seq DEA were not represented in the final 4322 Microarray gene list due to the merging of Affymetrix gene list (whose annotation file was also used for RNA-Seq annotation) with that of Agilent's. One could argue that the use of Agilent dataset may not have been necessary. However, besides the obvious reason that including the Agilent dataset increases the sample size (which is one of the fundamental premises for a more successful integrative data analysis), another reason is that the results one might get from excluding the Agilent dataset might be biased towards the popularity of the Affymetrix platform. Therefore, by analyzing different platforms of Microarray technology as well as similar versions of the same Illumina RNA-Seq platform, we probably minimized any such bias.

While the utilized cross-platform normalization (merging) methodology works quite well for robust biomarker discovery, there are some inherent limitations to be recognized. Despite our successful efforts to minimize between-laboratory heterogeneity (batch effects) across experiments, the merging method cannot guarantee the complete removal of such effects. Moreover, integrative analysis methods may provide power through increased sample size at the expense of the analyzed number of genes. Genes which are not common in all integrated platforms are lost, and consequently, a decline in the number of genes to be analyzed was observed. Although the results were concordant with the literature and consistent within and between both technologies, the quality of the deposited, original data may be a limiting factor for having the most accurate, statistically sound results.



### **Chapter 5**

# **Conclusion**

To our knowledge, this thesis describes the first technical approach for integrative publicly available Microarray and RNA-Seq axolotl data analyses, aiming at unraveling differentially expressed genes marking the wound healing and regenerative phases of the axolotl limb. The Microarray and RNA-Seq DEAs showed consistent results manifested in the same pattern of distribution of DE genes, as well as the positive correlation of the DE genes and the top DE genes commonly identified by both technologies, across the wound healing vs. control, regenerative vs. control, and regenerative vs. wound healing comparisons. Many of our top DE genes were previously identified as significantly differentially expressed, and their enrichment in a wide variety of biological processes was concordant with those described in previous studies. Some DE genes resulting from only RNA-Seq DEA also showed similar concordance. Future direction of this study would aim to functionally validate some of our top DE genes and perhaps identify some of them as biomarkers for the wound healing and regenerative phases of the axolotl limb. Besides, the described bioinformatic methodology can be further expanded to include various other statistical approaches, such as performing differential expression analysis among all experimental groups at once using the ANOVA test or the limma package, followed

by hierarchical clustering-based heatmap generation in order to have a unified visualization and interpretation of the data. We hope that our study provides enough confidence for researchers around the world to consider our DE lists for their functional studies and perhaps to integrate their data into our methodology in order to increase the sample size, and thereby obtaining even higher statistical confidence for biomarker discovery.



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# **Appendix**

# **Appendix A**

# **A.1 Microarray Axolotl Dataset Selection**










## **A.2 RNA-Seq Axolotl Dataset Selection**



GSE1 03087	GPL22800 Illumina HiSeq 2500 (Ambysto ma mexicanu m)	There are two conditions, with four biological replicates per condition. Condition 1 samples, "Multi-amp" in the sample names, are derived from axolotl limbs that have undergone six rounds of amputation-regeneration and mRNA was extracted at three days following the last amputation. Condition 2 samples, "Contol" in the sample names, are age- and size-matched sibling animals that have undergone a single amputation and mRNA was extracted at three days following this amputation.	Fastq	https://w ww.ncbi .nlm.nih .gov/geo /query/a cc.cgi?a $cc = GSE$ 103087	https:// www.e bi.ac.u k/ena/d ata/vie w/PRJ <b>NA400</b> 170
GSE9 2429	GPL22800 <b>Illumina</b> HiSeq 2500 (Ambysto ma mexicanu m)	Profiled 42 samples across 16 tissues, from distinct locations among intact and regenerating limbs, relevant cell types, and other progenitor-rich samples using RNA-sequencing	Fastq	https://w ww.ncbi .nlm.nih .gov/geo /query/a cc.cgi?a $cc = GSE$ 92429	https:// www.e bi.ac.u k/ena/d ata/vie w/PRJ <b>NA300</b> 706
GSE7 4372	GPL14997 <b>Illumina</b> Genome Analyzer <b>II</b> <sub>x</sub> (Ambysto ma mexicanu m)	Characterized microRNA expression during Axolotl forelimb regeneration using small RNA sequencing. The same samples were assayed for mRNA expression using mRNA sequencing. Small RNA and mRNA gene expression profiling during 0, 3, 6 and 14 days post amputation.	Fastq	https://w ww.ncbi .nlm.nih $.$ gov/geo /query/a cc.cgi?a $cc = GSE$ 74372	https:// www.e bi.ac.u k/ena/d ata/vie w/PRJ <b>NA299</b> 879
GSE3 4394	GPL14997 <b>Illumina</b> Genome Analyzer <b>II</b> X (Ambysto) ma mexicanu m)	performed deep RNA sequencing of the blastema over a time course. Then, compare the expression patterns to those in a mouse digit amputation model to identify genes specific to the regenerative response	Fastq	https://w ww.ncbi .nlm.nih .gov/geo /query/a cc.cgi?a $cc = GSE$ 34394	https:// www.e bi.ac.u k/ena/d ata/vie w/PRJ <b>NA149</b> 573

**Table A.2**: Description of the selected RNA-Seq datasets for integrative analysis



## **A.3 Detailed Information on Microarray Axolotl Data**

















	GSM894012 288h_lwp_rep2
	GSM894013 528h_lwp_rep2
	GSM894036 72h_lwp_rep3
	GSM894037 120h_lwp_rep3
	GSM894038 168h_lwp_rep3
	GSM894039 288h_lwp_rep3
	GSM894040 528h_lwp_rep3
GSE37198	GSM913393 Innervated limb at D3, biological rep1
	GSM913394 Innervated limb at D3, biological rep2
	GSM913395 Innervated limb at D3, biological rep3
	GSM913396 Innervated limb at D3, biological rep4
	GSM913405 Innervated limb at D7, biological rep1
	GSM913406 Innervated limb at D7, biological rep2
	GSM913407 Innervated limb at D7, biological rep3
	GSM913408 Innervated limb at D7, biological rep4
	GSM913397 Flank wound at D3, biological rep1
	GSM913398 Flank wound at D3, biological rep2
	GSM913399 Flank wound at D3, biological rep3
	GSM913400 Flank wound at D3, biological rep4
	GSM913409 Flank wound at D7, biological rep1
	GSM913410 Flank wound at D7, biological rep2
	GSM913411 Flank wound at D7, biological rep3
	GSM913412 Flank wound at D7, biological rep4

**Table A.3**: Detailed information on possible GSM accession, timepoint, amputation/injury site, and replicate number of each sample from Microarray data as reported in GEO

## **A.4 Detailed Information on RNA-Seq Axolotl Data**





**Table A.4**: Detailed information on possible GSM accession, timepoint, amputation/injury site, and replicate number of each sample from RNA-Seq data as reported in GEO



## **A.5 Top DE Genes from Both Technologies**














































**Table A.5**: List of the top DE genes commonly identified by Microarray and RNA-seq platforms for all three comparisons















Table A.6: Gene ontology terms enriched by the top 91 DE genes in wound healing vs. control comparison, commonly identified by both the analysis of both technologies



## **A.7 GO Terms Enriched in Regenerative vs. Control**









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**Table A.7**: Gene ontology terms enriched by the top 351 DE genes in regenerative vs. control comparison, commonly identified by the analysis of both technologies

## **A.8 GO Terms Enriched in Regenerative vs. Wound healing**





















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**Table A.8**: Gene ontology terms enriched by the top 280 DE genes in regenerative vs. wound healing comparison, commonly identified by the analysis of both technologies

## **Appendix B**

## **B.1 Microarray Axolotl Data Processing Workflow**



**Figure B.1**: Detailed workflow for Affymetrix and Agilent Microarray axolotl data processing prior to differential expression analysis

## **B.2 RNA-Seq Axolotl Data Processing Workflow**



**Figure B.2**: Detailed workflow for Illumina RNA-Seq data processing prior to differential expression analysis

## AN INTEGRATIVE GENE-EXPRESSION ANALYSIS OF AXOLOTL LIMB WOUND HEALING AND REGENERATION



Kunej. "Pivotal role of the muscle-contraction

pathway in cryptorchidism and evidence for

genomic connections with cardiomyopathy