NAIST-IS-DD1361018

## **Doctoral Dissertation**

# **Curcuminoid Synthesis Pathway Analysis Based on Integration of RNA -seq and Metabolite Data**

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September 1, 2015

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A Doctoral Dissertation submitted to the Graduate School of Information Science, Nara Institute of Science and Technology in partial fulfillment of the requirements for the degree of Doctor of Science. Li Donghan

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### **Curcuminoid Synthesis Pathway Analysis Based on Integration of RNA-seq and Metabolite Data \***

#### **Li Donghan**

#### **Abstract**

Curcuminoids are secondary metabolites that act as the primary active constituents of turmeric. To understand the curcuminoids synthesis pathway, we compared two wild strains and two cultivars to understand the differences in the synthesis pathway. Because the fluxes of metabolic reactions depend on the amounts of their substrate and the activity of the catalysts, we analyzed the metabolite concentrations and gene expression of the enzymes. The RNA sequencing (RNA-seq) analysis based on Next-Generation Sequencing (NGS) technology was applied to detect gene expression level. By comparing the genes expression level corresponding to both leaves and rhizomes of 4 specimens (*Curcuma aromatica*, *Curcuma longa*, *Curcuma longa* cultivars Sekiyou, *Curcuma longa* cultivars Ougon), we determined the genes for which expression level significantly changes between the leaves and rhizomes. We next focused on the metabolic pathway that synthesizes curcuminoids, in order to understand the difference in curcuminoids concentrations among the four specimens. We developed a 'selection first' method for RNA-seq analysis in which short reads are mapped to selected enzymes in the biosynthetic pathways in order to reduce the effect of mapping errors. Using this method, we found that there were significant changes in expression levels of the enzymes at the branching point of the curcuminoids biosynthesis pathway, which is consistent with the observed curcuminoids contents. By the high expression level of phenylpropanoylacetyl-CoA enzymes, p-coumaroyl-CoA is expected to synthase in a fast reaction speed and make the synthesis flux to the largest accumulation of demethoxy curcumin in *Curcuma longa* cultivars Ougon and *Curcuma longa aromatica.* While in the other group (*Curcuma longa* cultivars Sekiyou and *Curcuma longa*), low expression level of phenylpropanoylacetyl-CoA results in more accumulation of feruloy-CoA instead of demethoxy curcumin. The high expression level of curcumin synthase enzymes in the following reaction steps synthesize the largest amount of curcumin.

#### **Keywords:**

metabolite analysis, RNA-seq, NGS, curcumin, gene expression analysis,

<sup>\*</sup>Doctoral Dissertation, Department of Information Science, Graduate School of Information Science, Nara Institute of Science and Technology, NAIST-IS-DD1361018, September 25, 2015.

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## **Chapter I. Introduction**

This doctor dissertation explained the author's research and results on the research subject: applying the next-generation sequencing (NGS) technique and gas chromatography - mass spectrometry (GC - MS) simultaneously on the analysis of the metabolomics.

The purpose of this study is to analyze the metabolite biosynthesis pathway and understanding the metabolite synthesis mechanism. The metabolites are affected by the network of synthesis reactions and expression level of enzymes. The bio-reaction network would decide synthesis process. The enzymes expression level controls the bioreaction's rate. In this study, we choose turmeric (*Curcuma longa*) as study object and four cultivars of turmeric are selected as samples. We compare the concentration of main secondary metabolite of the samples by the GC-MS to determine the metabolite difference between the samples. On the other hand, we use NGS technique to determine the transcriptome of each sample. Not only the enzyme sequence alignment but also the enzyme expression level can be determined. The metabolite changes among the 4 samples, while the enzymes are up-regulated or down-regulated differently compared with each other sample. We found that the metabolite difference between the samples can be interpreted by the gene expression level changes between the 4 cultivars. The upregulated or down-regulated genes affect the bio-synthesis reactions; leading to the different reaction flow; and finally cause the metabolite changes among the samples.

When NGS technique initialized to transcriptome analysis, first the gene sequences will be assembled from short reads. Then all the raw short reads will be mapped to the

assembled gene sequences to calculate the short read abundance of each gene sequence which will be gene expression level. According to the purpose of the research, a specific gene set of the transcriptom will be selected by and the gene expression level will be determind. The workflow is suitable and generally applied in whole transcriptom and genome analysis. It can be called ' mapping first, select later' mapping strategy. But when this 'mapping first' strategy applied to a limited gene set (for example the secondary metabolic pathway genes), the mapping result will be inaccurate for that in the mapping stage, compare with the targeted gene set, large numbers of whole transcriptom genes involve in and mapping gene template is not accurate. To avoid this, we develop a 'select first' mapping strategy in this study. For the secondary metabolic pathway gene analysis, we firstly select a targeted gene set and then map all the raw reads to the selected genes. This method lowers the coefficient of variation (CV) of estimated expression level of selected genes from 2.12 to 1.47 compared with the 'mapping first' strategy. We also validated this strategy by applying on four kinds of housekeeping genes. The CVs of these housekeeping genes out of smaller range.

### **1.1 Turmeric and curcuminoid**

During the past decades, there has been increasing demand of the new medical technology and new drug to the pharmaceutical research and development. Nowadays, the new drug developing requires more developing time and cost. The Tufts Center for the Study of Drug Development (TCSDD) has conducted several studies of drug development times, which indicate that the total time from synthesis (of a compound) to approval of a New Drug Application (NDA) for self-originated New Chemical Entity (NCE) has increased significantly, from an average of 7.9 years in the 1960s to 12.8 years in the 1990s **[Fig 1.1]** (Michael et al. 2004). Much of the increase in drug development time is due to increased time for the clinical trial portion of the process. Also clinical testing is the most costly component of drug discovery, with the costs



**Figure 1.1** Total time cost from synthesis (of a compound) to NDA approval. (Figure adapted from Michael et al. 2004)

in each successive phase clinical testing is the most costly component of drug discovery, with the costs increasing in each successive phase **[Fig 1.2]** (Michael et al. 2004). Phase I corresponds to a 30 days of clinical trials in human. A small number of normal, healthy volunteers are conducted and safe dose is determined. Phased II, large number samples of volunteers who have the production's medical condition are intended to treat. In Phase III, large number of patients are involved. Phase III expected costs are 44% higher than Phase I. Although animal testing costs are less than those for clinical trials, the total cost of these tests is not trivial. Meanwhile the risk of the side effect became more and more uncontrollable. Because of the increasing cost of the new drug development, more and more pharmic researchers are turning into the traditional herbal medicine research.

Traditional herbs are used in many countries for centuries, for example Traditional Chinese Medicine in China, Kampo in Japan, Jamu in Indonesia (Borchers et al. 2000; Afendi et al. 2012; Tan et al. 2004). Compare with modern medicine, traditional herbs have been used for a long time and have been improved. Most herbal medicines are derived from wild plant product and they are the mixture of multiple plant secondary metabolites. Hence plant secondary metabolomics is the key to understand the biosynthesized mechanism of medicinal components in the plants.

Turmeric (*Curcuma longa*) is a tropical plant in the family Zingiberaceae **[Fig. 1.3A]**. This genus has been considered originating in the Indo-Malayan Region (Purseglove, 1968) and has widespread occurrence in the tropics of Asia to Africa and Australia. Out of the 100 or so species were reported in the genus, and about 40 of them are of Indian origin (Velayyudhan *et al.,* 1999). The powdered rhizome of turmeric **[Fig 1.3B]** has been used widely as a spice especially in traditional Asian dishes, as a traditional medicine, and also as a bright yellow dye (Jayaprakasha et al. 2005). Traditional Indian Ayurvedic and Sidha systems of medicine have recognized the medicinal value of turmeric in its crude form since very ancient times. The last few decades have witnessed extensive research interests worldwide in the biomedical activity of turmeric and its compounds. Thus *Curcuma* is now gaining importance all over the world as a mighty



**Figure 1.2** Expected cost/NCE of research phases. (Figure adapted from Michael et al. 2004)



**Figure 1.3** *Curcuma longa* plant, the rhizome, and the powdered rhizome.

cure to combat a variety of ailments, as the genus carries molecules credited with antiinflammatory, hypocholestraemic, choleratic, antimicrobial, antirheumatic, antifibrotic, antivenomous, antiviral, antidiabetic, antihepatotoxic and anticancerous properties as well as insect repellent activity (Chattopadhyay et al. 2004). A US Patent (No. 20030185907) is now in place on a method of treatment of inflammation and pain in mammals including human beings using curcuminoids along with other plant-derived molecules. Turmeric oil is also now used in aromatherapy and the perfume industry. Turmeric powder has healing effect on both aseptic and septic wounds in rats and rabbits (Gujral et al. 1953). And it also shows adjuvant chemoprotection in experimental forestomach and oral cancer models of Swiss mice (Azuine et al. 1994). A research of indomethacin-induced gastric ulcer caused by reactive oxygen species shows the gastroprotective effect of curcumin thereon (Chattopadhyay et al. 2005).

Curcumin is known as the main medicinal ingredient, and its analogs **[Fig 1.4]** curcuminoids—also show useful bioactivity (Maheshwari et al. 2006). Various species in the genus *Curcuma* synthesize curcuminoids, and their contents and activities vary greatly (Sasikumar 2005; Lobo et al. 2009; Wang Y, et al. 1999). Jayaprakasha studied the variation of three curcuminoids in four different commercial varieties of turmeric, namely 'Salem', 'Erode', 'Balasore' and 'Mysore'. The percentage of curcumin, demethoxy curcumin and bis-demethoxy curcumin were found to be  $1.06 + 0.061$  to 5.65  $\pm$  0.040, 0.83  $\pm$  0.047 to 3.36  $\pm$  0.040 and 0.42  $\pm$  0.036 to 2.16  $\pm$  0.06, respectively in the four samples (Jayaprakasha et al. 2002). The total percentages of curcuminoids are  $2.34 \pm 0.171$  to  $9.18 \pm 0.232$ . The curcumin contents among subspecies of *C. longa* vary from high (more than 1800mg/100gDW) to low (50~100mg/100gDW) (Toshikazu et al. 2006). Therefore, understanding the bioproduction of these different analogs in the species of the genus *Curcuma* will provide valuable information for its medicinal applications. Currently, because of the increasing demand in the pharmaceutical and food industries, there is a pressing need (Kinghorn, A. et al. 2011) to understand the dynamics of the productivity of curcumin and curcuminoids in the genus *Curcuma*. To understand the differences in metabolic

production between species and cultivars, both the amounts of substrates and the activities of enzymes provide important clues.

In this study, we focused on the analysis of metabolite concentrations and gene expressions of enzymes in the curcuminoids biosynthesis pathways. To date, several attempts at crop improvement for turmeric have been performed to increase yield potential and to enhance the amounts of active ingredients such as curcuminoids and the sesquiterpenoids (Ravindran et al. 2007). Turmeric, however, is a cross-pollinated triploid species, which indicates its scarce pollen fertility. They were propagated traditionally by underground rhizomes and thus crop improvement programs in turmeric were largely restricted to clonal selection or induced mutations with subsequent selection. Even though there is a long history of turmeric cultivation, only a few improved varieties of turmeric are recognized in Japan. Recently, some cultivars of turmeric with higher contents of curcuminoids than the wild-type *C. longa*, were registered in the Japanese Plant Variety Protection facility (Ministry of Agriculture, Forestry and Fisheries, Tokyo Japan). *C. longa* 'Ougon,' a commercial cultivar, was bred in Okinawa, and *C. longa* 'Sekiyo,' another commercial cultivar, was originally discovered in Southeast Asia.

Curcumin [1,7-bis-(4-hydroxy-3-methoxyphenyl)hepta-1,6-diene-3,5-dione] **[Fig. 1.4]** is isolated as the pigment of the *C. longa* rhizome. It has wide variations in efficacy in anti-inflammatory, antiulcerogenic, and antitumor activities (Aggarwal et al. 2003). Demand for curcumin is rising because of its pharmaceutical usefulness as a dietary supplement. Curcuminoids, including de-methylated analogues of curcumin **[Fig. 1.4]**, have also received attention.

Curcuminoids are mainly accumulated in rhizomes of turmeric, resembling ginger roots. Here we focused on differences in curcuminoid contents among cultivars and analyzed gene expressions of their synthesizing enzymes to understand the metabolic reactions involved. We measured metabolite concentrations using liquid chromatography–mass spectrometry (LC-MS) and gas chromatography - mass spectrometry (GC-MS), and analyzed gene expressions using an RNA-Seq method (Wang et al. 2009), for rhizome samples of the two wild-type variants (*C. aromatic* abbreviated as AR) and *C. longa* (LN)) and two cultivars (*C. longa* 'Ougon' (OU), and *C. longa*, 'Sekiyo' (SK)).



Figure 1.4: Three analogs of curcumin.

### **1.2 Specimens and reagents**

Four samples of specimens utilized in this work are namely Okinawa *Curcuma longa*, Okinawa *Curcuma aromatica*, a new cultivar *Curcuma longa* 'Sekiyo' ("Sekiyo", Japanese Plant Variety Protection No. 21486), and another cultivar *Curcuma longa* 'Ougon' ("Ougon", Japanese Plant Variety Protection No. 21484) and be showed in **Table 1.1**. Three replicates of each specimen were planted in the Experimental Station for Medicinal Plant Research, University of Toyama following usual agronomical cultivation practices under the same conditions. The leaves and rhizomes were dug out after the aerial parts fully dried up. This period was considered as the initial period of dormancy. All specimens were deposited in the Museum of Materia Medica, College of Pharmaceutical Science, Ritsumeikan University (*C. longa*; Boucher No. RIN-CL-15, *C. aromatic*; Boucher No. RIN-CL-16, *C. longa*, Sekiyo; Boucher No. RIN-CL-17, *C. longa*, Okinawa Ougon; Boucher No. RIN-CL-18). All analytical grades of chemicals and LC-MS grades of chromatographic solvent reagents were purchased from Wako Chemical Co. Ltd (Tokyo, Japan). Standard compounds for HPLC quantitation of curcumin, demethoxy curcumin, and bisdemethoxy curcumin were purchased from Nagara Science Co. Ltd. (Gifu, Japan).

Sample name	Abbreviation	Data name from	Sample names in	Scientific name
		Toyama	Japanese	
		University		
Curcuma	<b>AR</b>	Toyama-univ 1	春ウコン 葉	Curcuma
aromatica_leaf				aromatica
Curcuma	<b>AR</b>	Toyama-univ_2	春ウコン 根	Curcuma
aromatica_root				aromatica
Curcuma	LN	Toyama-univ 3	秋ウコン 葉	Curcuma longa
longa_leaf				
Curcuma	LN	Toyama-univ 4	秋ウコン 根	Curcuma longa
longa root				
Curcuma	OU	Toyama-univ 5	皇金葉	Curcuma longa
ougon leaf				
Curcuma	OU	Toyama-univ 6	皇金根	Curcuma longa
ougon root				
Curcuma	<b>SK</b>	Toyama-univ_7	赤陽_葉	Curcuma longa
sekiyou_leaf				
Curcuma	<b>SK</b>	Toyama-univ 8	赤陽_根	Curcuma longa
sekiyou_root				

**Table 1.1** Four sample of specimens utilized in this work

### **1.3 Next Generation Sequencing**

#### *Transcriptome Analysis*

Transcriptome is the complete set of messenger RNA (mRNA) and noncoding RNA (ncRNA) transcripts produced by a particular cell, cell type, or organism. An intriguing problem in molecular biology is how the identical genetic make-up of cells can give rise to different cell types, each of which plays a defined role in the functioning of a multicellular organism. This phenotypic diversity has been linked to the fact that different cell types within the organism activate (or express) different sets of genes (transcriptomes) that lead to different cell fates and functions. The development of microarrays supplanted single-gene approaches by allowing simultaneous characterization of expression levels of thousands of known or putative transcripts (Sanger 1977). This method brought about a multitude of expression-profiling initiatives aiming to comprehensively characterize expression signatures of different cell types and disease states. Further developments in the microarray field enabled other transcriptomics applications, such as the detection of noncoding RNAs, single nucleotide polymorphisms (SNPs), and alternative splicing events (Mockler et al. 2005). Due to their cost efficiency, microarrays are a commonly used tool in transcriptomics research utilized in many laboratories around the world (Pozhitkov et al. 2007). However this method can not address several key aspects such as detect novel transcripts and ability to study the coding sequence of detected transcripts. Moreover, since microarrays are indirect methods in which transcript abundance is inferred from hybridization intensity rather than measured explicitly, the derived data are noisy, which interferes with reproducibility and cross-sample comparisons.

The development of expressed sequence tag (EST) sequencing in 1991 partially addressed the cost limitation of FLcDNA sequencing by introducing a less complete, less accurate, yet cheaper approach to the detection of expressed transcripts than was possible with sequencing full-length cDNA sequencing (FLcDNAs) (Boguski 1995). Despite the decrease in cost, however, EST sequencing with the Sanger method was still too expensive and labor intensive to be routinely used on a transcriptomewide scale. Moreover, due to the low redundancy of sequencing reads, EST data were not suitable for estimating transcript abundance.

The report of Serial Analysis of Gene Expression (SAGE) provided a key advance in transcriptome sequencing as it facilitated the use of Sanger sequencing for gene expression profiling (Velculescu VE, 1995). SAGE experiments offered many advantages over microarrays, such as the ability to detect novel transcripts, the ability to obtain direct measures of transcript abundance thus allowing easier comparisons between multiple samples, and the discovery of novel alternative splice isoforms. However, SAGE studies still involved a laborious cloning procedure, were costly, and produced short sequence tags (14 or 21 bp) that are difficult to resolve for transcripts with similar coding sequence.

As shown in **Figure 1.5**, Sanger sequencing was adopted as the primary technology in the "first generation" of laboratory and commercial sequencing applications due to its high efficiency and low radioactivity. At that time, DNA sequencing was laborious and radioactive materials were required. After years of improvement, Applied Biosystems introduced the first automatic sequencing machine (namely AB370) in 1987, adopting capillary electrophoresis which made the sequencing faster and more accurate. Since the early 1990s, DNA sequence production has almost exclusively been carried out with capillary-based, semi-automated implementations of the Sanger biochemistry (Shendure et al. 2008). This method is essentially tricking DNA polymerase into incorporating nucleotides with a slight chemical modification—the exchange of the 3′ hydroxyl group needed for chain elongation with a hydrogen atom that is functionally unable to participate in the reaction with the incoming nucleotide to extend the synthesized strand. Mixing proportions of the four native deoxynucleotides with one of four of their analogs, termed dideoxynucleotides, yields a collection of nucleotide-specific terminated fragments for each of the four bases (Sanger et al. 1977).



**Figure 1.5** Sanger sequencing (Figure adapted from Mardis et al., 2013)

Newer methods are referred to as next-generation sequencing (NGS) (Mardis et al. 2008). And the NGS technologies are different from Sanger method in many aspects such as massively parallel analysis, high throughput, and relative lower cost.

Following the human genome project, the first NGS DNA sequencer GS20 was launched to the market by 454 Life Science in 2005, and Solexa released Genome Analyzer the next year, followed by (Sequencing by Oligo Ligation Detection) SOLiD provided from Agencourt, which are three most typical massively parallel sequencing systems in the NGS that shared good performance on throughput, accuracy, and cost compared with Sanger sequencing (**Table 1.2**). These founder companies were then purchased by other companies: in 2006 Agencourt was purchased by Applied Biosystems, and in 2007, 454 was purchased by Roche, while Solexa was purchased by Illumina. After years of evolution, these three systems exhibit better performance and their own advantages in terms of read length, accuracy, applications, consumables, man power requirement and informatics infrastructure, and so forth (Lin et al 2012).

These newer technologies constitute various strategies that rely on a combination of template preparation, sequencing and imaging, and genome alignment and assembly methods. The arrival of NGS technologies in the marketplace has changed the way we think about scientific approaches in basic, applied and clinical research. In some respects, the potential of NGS is akin to the early days of polymerase chain reaction (PCR), with one's imagination being the primary limitation to its use. The major advance offered by NGS is the ability to produce an enormous volume of data cheaply — in some cases in excess of one billion short reads per instrument run. This feature expands the realm of experimentation beyond just determining the order of bases. For example, in gene-expression studies, microarrays are now being replaced by seq-based methods, which can identify and quantify rare transcripts without prior knowledge of a particular gene and can provide information regarding alternative splicing and sequence variation in identified genes.



## **Table 1.2** Comparison of 3 systems of NGS and Sanger method

The ability of sequencing the whole genome of many related organisms has allowed large-scale comparative and evolutionary studies to be performed that were unimaginable just a few years ago. The broadest application of NGS may be the resequencing of human genomes to enhance our understanding of how genetic differences affect health and disease (Bras et al. 2012; Gonzaga-Jauregui et al. 2012). The variety of NGS features makes it likely that multiple platforms will coexist in the marketplace, with some having clear advantages for particular applications over others. Although NGS makes genome sequences handy, the followed data analysis and biological explanations are still the bottle-neck in understanding genomes.

### **1.4 Bioinformatics**

In the RNA-Seq analysis, the whole transcriptome provides a huge number of short reads. In general, the raw reads are assembled to obtain expressed gene sequences and then each reads are aligned (mapped) to the assembled sequences first. Then following up reads count calculation reveals the expression level of the assembled sequences. For the short reads are from the whole mRNA of a cell, it contains all the gene information of the cell. The following up gene analysis focuses on the whole transcriptome/genome. Whole transcriptome analysis will give a all-round gene level information about the cell, which just correspond to the primary metabolic pathway analysis perfectly.

In chapter IV, we focus on a small scale of a secondary metabolic pathway -curcuminoid synthesis pathway, which is less complex and small scale compare with the major metabolic pathways. The traditional whole transcriptome analysis is not very suitable for a specific secondary metabolic pathway analysis. Though the NGS data from transcriptome contains the all gene information including curcuminoid synthesis pathway genes. Mapping the short reads to the whole transcriptome let the multifarious gene information from primary metabolic pathway overshadowed the genes which we

focused on. So we used a targeted mapping strategy--focusing on a small set of secondary metabolic pathway genes -- to analyze the gene expression.

To minimize analysis errors identified by measures such as read-quality control (Rismani-Yazdi et al. 2011, Patel and Mukesh 2012), we propose a "selection-first" RNA-Seq analysis, in which reads are mapped to particular biosynthetic pathways. Initially, we selected the gene sequences that were most homologous to the targeted gene sequences for known enzymes in the biosynthetic pathways of curcuminoids, and then we mapped the raw reads to the selected template sequences. Compared to the general "mapping-first" analysis in which all reads are mapped to the total assembled sequences by removing inaccurate templates, we expect to reduce the errors caused by misassembly and mismapping. This lowers the CVs of estimated expression levels of selected sequences.

# **Chapter II. Gene expression analysis**

## **2.1 NGS data prepare and work flow**

#### *NGS'analysis'background'*

The NGS technique can be applied for different research like nucleotide mutation types detection, transcriptome analysis, and so on. One of the most common use is transcriptom/genome analysis. To get the transciptome information from billions of NGS short reads, people assemble the short reads into transcriptome in 3 kinds of strategy: a reference-based strategy, a *de novo* assemble strategy or a combined strategy that merges the two.

When a reference genome for the target transcriptome is available, the transcriptome assembly can be built upon it. In general, this strategy — which is known as 'reference-based' or 'ab initio' assembly — involves three steps. First, RNA-seq reads are aligned to a reference genome using a splice-aware aligner. Second, overlapping reads from each locus are clustered to build a graph representing all possible isoforms. The final step involves traversing the graph to resolve individual isoforms. With the reference-based transcriptome strategy, assembly can be solved uing parallel computing and requirement of the computer server is not too much. More importantly, the reference-based strategy is very sensitive and can assemble transcripts of low abundance (Jeffrey 2011).

The '*de novo*' transcriptome assembly strategy does not use a reference genome: it leverages the redundancy of short-read sequencing to find overlaps between the reads

and assembles them into transcripts. The '*de novo*' assembly can provide an initial set of transcripts for it does not depend on any reference genome, allowing for RNA-seq expression studies. A second advantage of *de novo* assembly is that it does not depend on the correct alignment of reads to known splice sites (Burset et al. 2000) or the prediction of novel splicing sites, as required by reference-based assemblers.

To analyze the curcuminoid synthesis pathway mechanism, we select 4 cultivars (SK, OU, AR and LN as shown in **Table 1.1**) of turmeric.

We focused on the two cultivars, SK and OU by comparing them with the wild types to understand quantitative balances of curcuminoid biosynthesis in order to obtain clues for more efficient production of curcumin and curcuminoids. We analyzed the metabolite concentrations and gene expressions of these four specimens to clarify the relationships between species by curcuminoid metabolic pathway.  $Poly(A) + RNA$  was isolated from the frozen rhizomes from each specimens and cDNA libraries were constructed; the detailed protocol was described in (Suzuki 2004). The cDNA library was sequenced using the paired-end method with an Illumina HiSeq 1000 platform (Illumina Inc., San Diego, CA, USA). Each fragment was sequenced to a read length of 100 nucleotides from each end and we obtained more than 144 million pair reads. We used Trinity software (Grabherr et al. 2011) to assemble these reads to form scaffolds. The beginning of the curcuminoid synthesis is from more basic synthesis pathway such like glycolysis, and we also get 4 kinds of turmeric cultivates NGS short read data both from leaves and rhizomes. We use Trinity to assemble the short reads. **Table 2.1** shows the summary of the original data and assembling.

After getting the original NGS data of leaves and rhizomes from all 4 specimens, we used Trinity platform (http://trinityrnaseq.github.io/ Grabher, et al. 2011) to assemble the whole genome. Generally after the assembling of raw reads, all the reads would be mapped to the assembled sequences to calculate the sequence expression level. For all the reads are abstracted from all the mRNA/cDNA, this method is naturally used as genome/transcriptom analysis.

Sample name	Read numbers	Size	
AR leaf	$9917832 \times 2$	5.23GB	
AR root	$6706886 \times 2$	3.53GB	
LN leaf	$6950578 \times 2$	3.66GB	
LN root	$8829693 \times 2$	4.65GB	
OU leaf	$8685678 \times 2$	4.58GB	
OU root	$11669887 \times 2$	6.15GB	
SK leaf	$12647947 \times 2$	6.67GB	
SK root	$8987480 \times 2$	4.74GB	
Total	$74395981 \times 2$	39.21GB	

**Table 2.1** 8 samples original NGS data from 4 specimens of *Curcuma longa*

### **2.2 Gene differential analysis between leaf and rhizome**

#### *Select genes with significantly change in expression level*

The leaf is considered as the most active part of the whole plant. Many primary metabolic synthesis pathways like ATP, nucleotide, photosynthesis etc. are processed in the leaves. The curcuminoids are accumulated in the rhizome. The differences of gene expression level between in the leaf and rhizome will reveal the metabolic pathway diversity. We use NGS data from all 8 samples (4 are leaf data and 4 are rhizome data) to compare the gene expression changes between leaves and rhizome.

We use all 8 samples reads together to assemble the transcriptome. The Trinity assembler produce 302331 scaffolds. To eliminate redundant scaffolds (with tiny sequence difference only between the scaffolds) in the assembled scaffolds set, we clustered the scaffolds by Usearch software (http://www.drive5.com/usearch/; Edgar et al. 2010) and produce 192056 clustered scaffolds. Then the short reads of 8 samples were mapped to these 192056 scaffolds to identify the gene expression level of these 8 samples. The working flow is shown in **Figure 2.1**. Step 1, we firstly use 8 samples from both leaves and rhizomes of 4 cultivars to get sequenced by Illumina Hi-seq 1000 (Illumina Inc., San Diego, CA, USA). More than 74 million short reads are obtained by NGS. Step 2, We get 302311 assembled sequences scaffolds from 8 samples short reads together. The assembled sequence is called "scaffold". Step 3, the Trinity assembled scafflolds are clustered by Usearch software (http://www.drive5.com/usearch/; Edgar et al. 2010), 192056 clustered scaffolds were selected. Step 4. Mapping 8 samples short reads to the clustered scaffolds separately. Step 5. The scaffold expression level was calculated by FPKM package from Trinity kit. The mapping result shows that the gene expression levels of different samples are different.

To compare the difference between the leaf and rhizome, the gene expression level ratio between the leaf and rhizome is calculate by using the following equation:

$$
Genei ratio = \frac{Genei expression level in leaf}{Genei expression level in rhizome}
$$
 (1)

where *i* is from 1 to 192056 to represent the clustered scaffolds.

To calculate the ratio of the expression level of each gene, we firstly get rid of the genes which have 0 expression level records both in leaves and rhizome, which means the genes might be absent in the species. After removing the none-expressed genes separately from 4 cultivars, around 100000 scaffolds left for each cultivar (AR 94845 scaffolds, LN 97305 scaffolds, OU 92778 scaffolds, SK 103098 scaffolds left).

The gene ratio shows the extent of expression difference between the leaf and rhizome in a cultivar. We focused on especially high or low gene ratio which shows different biosynthesis pattern of a cell. Since the distribution of gene ratio can be approximated by Gaussian distribution [**Fig. 2.2**], we applied Z-test to evaluate significantly up/down regulated genes. To identify the significantly changed gens we set the  $H_0$ : gene expressed significantly high in the leaf compare with that in the root. Considering that around 100000 genes expressed for all 4 cultivars, we use a relatively strict threshold  $= 1/100000$  for a doubled sided significance test. We selected the gene with gene ratio fold change (FC) bigger than 1 with the confidence level *p*-value smaller than  $10^{-6}$ . The summary of significant genes shows in **Table 2.2, Figure 2.3**.



**Figure 2.1** Work flow of NGS data preparation. NGS data from 4 specimens 8 sample is assembled and gene expression level is calculated.



**Figure 2.2** Example of *C. longa* ougon of genes expression level ratio distribution. We calculate the expression of each gene first. Then expression ratio between the leaf and root is shown as the histogram. The blue line is the FC ratio distribution. The blue dash lines are the confidence interval of significant FC with *p*-value equals 1/100000. By selecting the genes which appear out of the blue line range we can pick up the genes which expression significantly change between leaf and rhizome.

	AR	LΝ	OU	<b>SK</b>
Genes No.*	94845	97305	92778	103098
High express in leaf	864	1880	2015	1303
High express in rhizome	706	1230	1355	1049
Mean of the ratio distribution	0 3 4 3	0.470	0.369	0.156
Sd of the ratio distribution	2 0 9 2	1911	1 705	1 822

Table 2.2 Gene expression selection based on ratio = leaf/rhizome

\* We removed the genes that show 0 expression in both leaf and rhizome in every specimen.


**Figure 2.3** The histograms with single peak show the ratio distribution between leaf and root that all genes express both in leaf and root. The histograms with 3 peaks show the ratio distribution that the genes express level can be 0 either in leaf or root. For the expression level 0 can not be calculated by the gene ratio, we change all 0 expression to 0.01. That leads to the 2 more peaks. The red dash line indicates the mean of each sample, and the blue dash lines indicate the threshold of 1/100000. The genes exist between the blue dash lines are considered not change significantly enough. And genes outside the blue dash lines are selected as significant change genes.

### **2.3 Major metabolite pathway analysis**

### *Mapping the significant genes to the major pathway*

In biochemistry, a metabolite pathway is series of chemical reactions that modified the initial chemical compounds into diverse of product compounds in a cell. All these reactions are catalyzed by enzymes. The product of one reaction is catalyzed as the substrate for next step reaction. These enzymes often require dietary minerals, vitamins and other cofactors to function. Pathways are required for the maintenance of homeostasis within an organism and the flux of metabolites through a pathway is regulated depending on the needs of the cell and the availability of the substrate. The end product of a pathway may be used immediately, initiate another metabolic pathway or be stored for later use. The metabolism of a cell consists of an elaborate network of interconnected pathways that enable the synthesis and breakdown of molecules. The metabolic pathway plays import role in cell. Every metabolic pathway consists of a series of biochemical reactions that are connected by their intermediates: the products of one reaction are the substrates for subsequent reactions, and so on. Metabolic pathways are often considered to flow in one direction. Although all chemical reactions are technically reversible, conditions in the cell are often such that it is thermodynamically more favorable for flux to flow in one direction of a reaction.

To annotate the gene function we compared the all clustered scaffold to the *Arabidopsis* genome by BLAST software (http://blast.ncbi.nlm.nih.gov/Blast.cgi; Altschul et al. 1990). After annotation of each scaffold, the information of genes whose expression level significantly changes can be obtained from KEGG database (KEGG; http://www.genome.jp/kegg/; Kanehisa et al. 2000). The bio-reaction which is catalyzed by the scaffold is recorded. Then the bio-reaction can be cataloged by the pathway. Here is a 2-step mapping: from scaffold to reaction, and then to the pathway. All the genes that up-regulated in the leaf among 4 specimens are cataloged into 118 pathways **[Table 2.3]**.

No.	Pathway	Pathway description	Up-reg gene No.	Total gene No.
$\mathbf{1}$	ath00500	Starch and sucrose	17	990
		metabolism		
$\overline{2}$	ath00520	Amino sugar and	16	696
		nucleotide sugar		
		metabolism		
3	ath01100	Metabolic pathways	185	8378
4	ath01110	Biosynthesis of secondary	82	4600
		metabolites		
5	ath00600	Sphingolipid metabolism	7	189
6	ath04075	Plant hormone signal	18	1198
		transduction		
7	ath04144	Endocytosis	9	779
8	ath04120	Ubiquitin mediated	14	646
		proteolysis		
9	ath00260	Glycine, serine and	11	283
		threonine metabolism		
10	ath00630	Glyoxylate and	11	317
		dicarboxylate metabolism		
11	ath01130	Biosynthesis of antibiotics	46	1938
12	ath00330	Arginine and proline	9	293
		metabolism		
13	ath01230	Biosynthesis of amino	31	1116
		acids		
14	ath03008	Ribosome biogenesis in	9	387
		eukaryotes		
15	ath03010	Ribosome	34	1863

Table 2.3 All up-regulated genes in leaf refer to 118 pathways.













To understand the difference between the 4 cultivars, the significantly changed genes are considered from every cultivar **[APP. Table 1-4]**. After the BLAST selection, the scaffolds that are with function annotation based on homologous genes are kept. Then by searching the KEGG database we confirm the pathway to which the annotated scaffolds can be refereed. From the Appendix Tables, inspect the genes appearance in every cultivar. We specially focus on 4 pathways that have close relationship to the next secondary metabolic pathway of curcuminoid: carbon fixation in photosynthetic organisms, glycolysis metabolic pathway, phenylalanine synthesis pathway and pentose phosphate pathway.

AR: The genes which in Carbon fixation in photosynthetic organisms pathway, and in the primary synthesis of the phenylalanine synthesis, have a high expression level change ranking in NADP-dependent malic enzyme 2 (NADP-ME2), glyceraldehyde 3-phosphate dehydrogenase (GAPCP-2), glyceraldehyde 3-phosphate dehydrogenase (GAPC2), malate dehydrogenase 1 (mMDH1) and fructose-1,6 bisphosphatase (HCEF1) (**[APP. Table 1]** row 26, 36, 38, 93 and 116). We also find genes of glyceraldehyde 3-phosphate dehydrogenase (GAPCP-2), glyceraldehyde 3 phosphate dehydrogenase (GAPC2), fructose-1,6-bisphosphatase (HCEF1) have a significant change in glycolysis pathway (**[APP. Table 1]** row 36, 38, 116) that are also related to the phenylalanine synthesis.

LN: For Carbon fixation in photosynthetic organisms pathway, there are 6 genes: NADP-dependent malic enzyme 2 (NADP-ME2), malate dehydrogenase (MDH), phosphoenolpyruvate carboxylase 1 (PPC1), malate dehydrogenase 1 (mMDH1), ribose 5-phosphate isomerase A, fructose-1,6-bisphosphatase (HCEF1) (**[APP. Table 2]** row 21, 33,71, 87, 142, 161) have been found up-regulated in the leaf. And 4 expression level changed genes: NADP-dependent glyceraldehyde-3-phosphate dehydrogenase (ALDH11A3), aldehyde dehydrogenase 3I1 (ALDH3I1), fructose-1,6-bisphosphatase (HCEF1), pyruvate dehydrogenase E1 beta (MAB1) (**[APP. Table 2]** row 38, 88, 161, 182) found in Glycolysis pathway.

OU: Four phenylalanine related genes are found up-regulated in the leaf: anthranilate synthase component I-2 (ASA2), tryptophan synthase beta chain (TSB2), bi-functional dehydroquinate-shikimate dehydrogenase (MEE32), tryptophan synthase alpha chain (**[APP. Table 3]** row 22, 59, 122, 184). Also other pathways like Pentose phosphate pathway related genes: NADP-dependent glyceraldehyde-3-phosphate dehydrogenase (ALDH11A3), transketolasek, Aldolase-type TIM barrel family protein (**[APP. Table 3]** row 56, 89, 111), Carbon fixation in photosynthetic organisms genes pathway genes: NADP-dependent malic enzyme 2 (NADP-ME2), alanine aminotransferase (AlaAT1), transketolase, fructose-bisphosphate aldolase 2 (FBA2), malate dehydrogenase 1 (mMDH1) (**[APP. Table 3]** row 12, 61, 89, 178,193), Glycolysis pathway genes: NADP-dependent glyceraldehyde-3-phosphate dehydrogenase (ALDH11A3), pyruvate dehydrogenase E1 beta (MAB1), plastidial pyruvate kinase 1 (PKP-ALPHA), 6-phosphofructokinase 3 (PFK3), FBA2; fructosebisphosphate aldolase 2 (FBA2) (**[APP. Table 3]** row 56, 104, 131, 174, 178) are significantly changed genes in the leaf compare with in the rhizome.

SK: There are a lot of Carbon fixation in Photosynthetic organisms related genes: NADP-dependent malic enzyme 2 (NADP-ME2), ribose 5-phosphate isomerase A, phosphoenolpyruvate carboxykinase [ATP] (PCK1), phosphoenolpyruvate carboxylase 1 (PPC1), malate dehydrogenase 1 (mMDH1) (**[APP. Table 4]** row 21, 40, 45, 48, 90) and Pentose phosphate pathway related genes: ribose-phosphate pyrophosphokinase 2 (PRS2), ribose 5-phosphate isomerase A, glucose-6-phosphate dehydrogenase 1 (G6PD1), PRS2; ribose-phosphate pyrophosphokinase 2 (PRS2) (**[APP. Table 4]** row 23, 40, 88, 115) found up-regulated in the leaf.

### *Analysis of curcuminoid synthesis genes in major metabolite pathways*

The RNA-seq based on NGS technology provides the whole transciptome of a cell. Not only the major metabolite pathway gene sequences but also secondary metabolite pathway genes also can be detected. Compare with the major metabolite pathway, secondary metabolite pathway would affect the final products more directly. We made a preliminary research on the curcuminoid synthesis genes analysis in major metabolite pathway analysis.

The curcumionid synthesis pathway from phenylalanine to curcumin and its analogs is available from KEGG (http://www.genome.jp/kegg/; Kanehisa et al. 2000) and MetaCyc (http://www.metacyc.org/; Caspi, et al 2008) database. Curcuminoid synthesis pathway refers to 11 different bio-reactions though only 4 out of these 11 reactions' enzymes/genes are identified in turmeric (CURS1, CURS2, CURS3, CUS). For other genes, we choose homologous genes from other species (ath: Arabidopsis thaliana, gmx: Glycine max, osa: Oryz sativa, zma: Zea mays), which catalyze the same reactions. The 11 genes are showed as **Table 2.4**.

Because of the curcumionds are accumulated in the rhizome, it is considered that the corresponding genes express high in the rhizome than in the leaf. We selected the FC of the express level of significantly changed genes in the rhizome **[Table 2.2]** (namely 706 up-regulated scaffolds in AR, 1230 in LN, 1355 in OU, and 1049 in SK). We compared these genes with 11 curcumin synthesis pathway genes with BLASTX and get 443 scaffolds annotated in total all through 4 cultivars **[App. Table 5]**. Some of the genes show significant FC in only one species but also there are genes shared by more than one species. **Figure 2.4** gives the detail information of the up-regulated genes in rhizome of all 4 cultivars.

enzyme	full name	KEGG reaction No.
PAL.	phenylalanine ammonia-lyase	4.3.1.24
4CL	4-coumarate: CoA ligase	$6.2.1 -$
C4H	cinnamate-4-hydroxylase	1.14.13.11
<b>HCT</b>	hydroxycinnamoyl transferase	2.3.1.133
C3H	cinnamate-3-hydroxylase	1.14.13.36
<b>OMT</b>	O-methyltransferase	2.1.1.104
<b>DCS</b>	phenylpropanoylacetyl-CoA synthase	2.3.1.218
<b>CURS1</b>	Curcumin synthase	2.3.1.217
<b>CURS2</b>	Curcumin synthase	2.3.1.217
<b>CURS3</b>	Curcumin synthase demethoxycurcumin synthase	2.3.1.217 2.3.1.219
CUS	bisdemethoxycurcumin synthase	2.3.1.211

**Table 2.4** 11 genes of curcuminoid synthesis pathway



**Figure 2.4** Venn diagram of 443 up-regulated genes in the rhizome among 4 cultivars are annotated by 11 curcumionoid synthesis pathway genes (namely 108 scaffolds in AR, 168 in LN, 191 in OU, and 128 in SK). There are 13 up-regulated genes shared by all 4 cultivars. And we also have a preliminary research on combination of LN and OU, which shared 24 up-regulated genes.

There are genes only up-regulated in a specific cultivar, and also some other genes have been found in 2, 3 or 4 cultivars. We summarized every possible combination and get all these genes annotated **[Table 2.5]**. Total 13 genes can be found up-regulated in the rhizome in all 4 cultivars.

We also have a preliminary research on the combination of LN and OU, which shared the most genes among all possible combinations. There are 24 genes found to be significantly up-regulated in the rhizome both in LN and OU. Among these 24 genes we found many genes appear in the same pathway: 2 genes for Ribosome; 2 genes for Oxidative phosphorylation; 2 genes for RNA transport, 2 genes for Plant circadian rhythm, 2 genes for Plant-pathogen interaction, 2 genes for Plant hormone signal transduction, 2 genes for Carbon metabolism. Considering the fact that we used a very strict threshold to distinguish significantly changed genes, LN and OU have many genes which can be found up-regulated in both of them. This fact shows that LN and OU have similar curcuminoid synthesis pattern. The statistical support will be discussed on the next step of research.

## **Table 2.5** Shared up-regulated genes in rhizome of 4 cultivars





 $AR + OU (7 genes)$ 



		acid aminotransferase 3	Valine, leucine and isoleucine biosynthesis;
			Pantothenate biosynthesis; and CoA
			Glucosinolate biosynthesis; Metabolic pathways;
			of secondary <b>Biosynthesis</b> metabolites;
			Biosynthesis of antibiotics; 2-Oxocarboxylic
			acid metabolism; Biosynthesis of amino acids
6		dehydratase-enolase-	Cysteine and methionine metabolism; Metabolic
		phosphatase complex 1	pathways
	7	ZTL; adagio protein 1	Circadian rhythm - plant

 $AR + SK$  (4 genes)



## $LN + SK$  (19 genes)







 $LN + OU (24 genes)$ 













 $AR + LN$  (8 genes)



 $AR + LN + SK$  (3 genes)





 $AR + OU + SK$  (3 genes)



 $LN + OU + SK$  (4 genes)











# **Chapter III. Rhizome gene expression analysis**

### **3.1 Introduction**

Curcuminoids mainly accumulate in rhizomes of turmeric, resembling ginger roots. Here we focused on differences in curcuminoids contents among cultivars and analyzed gene expressions of their synthesizing enzymes to understand the metabolic reactions involved. We measured metabolite concentrations using LC-MS and GC-MS, and analyzed gene expressions using an RNA-Seq method (Wang et al. 2009), for rhizome samples of the two wild-type variants.

### **3.2 Methodology**

#### *Analytical instruments*

LC-MS analyses were performed using a Shimadzu LC-IT-TOF mass spectrometer (Shimadzu Corp., Kyoto, Japan) equipped with an electrospray ionization (ESI) interface. ESI parameters were as follows: source voltage +4.5 kV, capillary temperature 200 °C, nebulizer gas flow rate 1.5 L/min. The mass spectrometer was operated in the positive ion mode scanning from m/z 50 to 2000. LC–MS was operated using a high-performance liquid chromatography mode or an infusion injection mode. A Waters Atlantis T3 column (2.1 mm i.d. × 150 mm) was used (Waters, Milford, MA, USA), and the column temperature was maintained at 40  $^{\circ}$ C. The mobile phase was a binary eluent of (A)  $0.1\%$  HCOOH solution and (B) CH<sub>3</sub>CN under the following

gradient conditions:  $0-30$  min linear gradient from  $20\%$  to  $100\%$  CH<sub>3</sub>CN,  $30-40$  min isocratic at  $100\%$  CH<sub>3</sub>CN. The flow rate was  $0.2$  mL/min.

For GC–MS analysis, a Shimadzu QP2010 mass spectrometer equipped with Shimadzu GC2010 gas chromatograph system was used (Shimadzu Corp.). The column was a fused-silica capillary column, DB-1 MS (30 m  $\times$  0.25 mm i.d., film thickness 0.25 µm). The injector and transfer line were maintained at 280 °C. The oven temperature was programmed as follows: initial temperature, 50 °C; initial hold, 2 min; temperature program rate, 10 °C/min; final temperature, 300 °C; final hold 10 min. The flow rate of the carrier gas (helium) was 1 mL/min. The following conditions were used for mass spectrometry: ionization, EI mode; ionization current, 60  $\mu$ A; ionization voltage, 70 eV. For GC–MS peak annotation, the KNApSAcK database (http://kanaya.naist.jp/KNApSAcK/; Afendi et al. 2012; Ikeda et al. 2013), NIST mass spectral database (http://www.nist.gov/srd/nist1a.cfm) and Wiley NBS mass spectral database were used.d

### *LC–MS sample preparation*

Frozen specimens were individually pulverized to a fine powder using a multibead shocker (Model MB755U, Yasui Kikai Co., Osaka, Japan). Two grams of fine powder from each sample was weighed accurately and sonicated for 30 min with methanol (20 mL). After centrifugation, each extract was filtered through a 0.2 µm Millipore filter (Millipore Corp., Billerica, MA, USA). One microliter aliquots of the solvent were injected into the LC–MS equipment.

#### *GC–MS sample preparation*

Frozen rhizomes from individual plant specimens were homogenized to a fine powder using a multibead shocker, as above. A subsample was transferred to a 10 mL glass tube and weighed to 100 mg. Five milliliters of ethyl acetate was added to the tube, and the sample was extracted under sonication for 30 min. After being centrifuged  $(10,000 \text{ g}, 2 \text{ min}, 4 \text{ }^{\circ}\text{C})$ , the organic solvent was collected.

#### *Strategy of RNA-Seq transcriptome for targeted metabolic pathways*

In general whole genome information analysis is not suitable for targeted gene network analysis. For this reason, we develop a targeted genes mapping strategy. We analyzed the expression of enzymes in the curcuminoid biosynthesis pathway by an RNA-Seq method using selection-first expression analysis according to the schematic illustration [**Fig. 3.1**] to the targeted metabolic pathways. Each raw read of the four specimens were mapped to the references to count the number of assigned reads. Finally, to estimate the expression level of each gene, the number of fragments per kilobase of exon per million fragments (FPKM) was computed using the method proposed by Li and Dewey (2011). When multiple scaffolds were assigned to an identical enzyme gene, we simply added all expression values. The final gene expression results are showed in Figure 3.2. There are two choices for the following step: a. general 'mapping first' strategy. Firstly all the short reads will be mapped to the assembled genome to calculate every gene expression level by FPKM. Then the homologous comparison by BLAST will be applied between the genome and the reference sequences to select target genes. Here we use 11 genes from curcuminoids synthesis pathway (**Table 2.4**). We use Coefficent of Variation (CV) to evaluate the efficiency of this 'select-first' method compared with the general 'mapping first' strategy. Below we discuss the steps of mapping first and select first strategy separately.

For the mapping first strategy **[Fig. 3.1A]**:

- 1. All the raw reads will be assembled to genome (by Trinity software).
- 2. The short reads are mapped to the assembled genome to calculate the every scaffold express level (FPKM value) in the genome (by Trinity software).
- 3. Homologous comparison between the genome and reference gene database by BLAST to select candidate scaffold. For each Gene  $i$  ( $i \in 1, ..., n$ ) from the reference gene database, there are always multiple scaffolds from assembled genome give good comparison hits. In this study the entries with the e-value smaller than  $10^{-40}$  will be kept as gene candidates for each reference gene. For each Gene *i* from reference gene set, scaffold<sub>(i,1)</sub>, scaffold<sub>(i,2)</sub>, ..., scaffold<sub>(i,m<sub>i</sub>)</sub>

are corresponding candidate sequence with the BLAST e-value smaller than  $10^{-40}$ . The scaffold<sub>(i,1)</sub>, scaffold<sub>(i,2)</sub>, ..., scaffold<sub>(i,m<sub>i</sub>)</sub> have corresponding FPKM value FPKM $(i,1)$ , FPKM $(i,2)$ , ..., FPKM $(i,m)$  respectively, which have already been calculated in Step 2. Notice that mi is the total number of scaffolds corresponding to Gene *i.*

4.

Mean<sub>i</sub> = 
$$
\frac{1}{m_i}
$$
 (FPKM <sub>(i,1)</sub> + FPKM<sub>(i,2)</sub> + ··· + FPKM<sub>(i,m<sub>i</sub>)</sub>) (1)

Standard Deviation 
$$
i = \sqrt{\frac{1}{m_i} \sum_{k=1}^{m_i} (FPKM_{(i,k)} - Mean_i)}
$$
 (2)

$$
CV i = \frac{Standard Deviation i}{Mean_i}
$$
 (3)

5. The average CV of all Gene  $i$  ( $i \in 1, ... n$ ) is:

$$
average CV = \frac{CV 1 + CV 2 + \dots + CV n}{n}
$$
 (4)

For the select first strategy **[Fig. 3.1B]**:

- 1. All the raw reads will assemble to genome (by Trinity software).
- 2. Homologous comparison between the genome and reference gene database by BLAST to select candidate scaffold. For each Gene  $i$  ( $i \in 1, ...n$ ) from the reference gene database, the entries with e-value smaller than  $10^{-40}$  will be kept as candidate scaffolds.
- 3. All the short read will be mapped to the candidate scaffold to calculate the expression level (FPKM). For every Gene  $i$  ( $i \in 1, ... n$ ), corresponding scaffolds are scaffold<sub>(i,1)</sub>, scaffold<sub>(i,2)</sub>, ..., scaffold<sub>(i,m<sub>i</sub>) and also the</sub> corresponding FPKM value:  $FPKM_{(i,1)}$ ,  $FPKM_{(i,2)}$ , ...,  $FPKM_{(i,m_i)}$
- 4. For each Gene *i*, we calculate the CV *i* in previous Step 4 Eq. (3).
- 5. The average CV of all Gene  $i$  ( $i \in 1, ..., n$ ) is calculated by Eq. (4).

The CV measures the extent of variability in relation to the mean of the population. Lower CV shows smaller error of the sample. Comparing with standard deviation, CV is useful because the standard deviation of data must always be understood in the context of the mean of the data. The actual value of the CV is independent of the data in which the measurement has been taken.

In this study a group of 11 genes **[Table 2.4]** from curcumiod synthesis pathway are selected as reference gene database. Out of them 4 genes are already identified in turmeric (CURS1, CURS2, CURS3, CUS). But for other 7 genes, we just use the homologous genes from other species like Arabidopsis thalina, Glycine max, Oryz sativa and Zea mays. The average CV of the estimated expression level (select-first strategy) for each enzyme was 1.47 **[Fig. 3.1B]**, whereas the average over the same enzyme was 2.12 when the raw reads were mapped to the whole scaffold first (mapping first strategy) **[Fig. 3.1A]**. We also make pairwise t-test of the gene expression CV and the *p*-value shows great significance ( $p$ -value = 0.002). The detail is shown below:





(In select-first strategy, only 2 scaffolds show similarity with CURS1 based on BLAST result. Because of the insufficient scaffolds we do not consider CURS1. So is the case of CURS1 and CURS2 in mapping first strategy. We also make pairwise t-test of the 2 strategies and calculate the *p-*value.)

We also validate the quality of expression analysis using the RNA-Seq method by evaluating expression levels of housekeeping genes. Four widely used housekeeping genes are selected as gene database as follows: glyceraldehyde 3-phosphate dehydrogenase, ubiquitin, tubulin, and elongation factor 1α (Guénin et al. 2008). We computed their expression levels to confirm that their expression levels do not vary among specimens. The CVs of these housekeeping genes among the four specimens ranged from 8.2% to 32.5%. It is worth noting that using the mapping-first analysis, the CVs of the same genes ranged from 12.8% to 46.2% and thus we could reduce the CVs by focusing on the specific pathways (select first strategy).



**Figure 3.1** The 11 genes average CV calculation workflow. **A** is the general 'mapping first strategy and the average CV is 2.12. **B** is the 'select first strategy. The average CV is 1.47.

For *Curcuma* genera, only an assembled collection of expressed sequence tags is available (Koo et al. 2013), and not their genome sequences. We first assembled the raw reads sequenced by the NGS to obtain the putative gene sequences of *Curcuma* species **[Fig. 3.2**, Step 1**]**. Because the differences in gene sequences among these specimens are not large, we first assembled the total raw reads of the four specimens together to obtain a shared reference sequence set **[Fig. 3.2**, Step 2**]**. In total, we obtained 30,200 scaffolds with an average *N50* value of 1379 bp.

Next, we searched for the gene sequences involved in the curcuminoid biosynthesis, because the whole genome of *Curcuma* has not been determined. The transcription associated with curcuminoid biosynthesis is also unavailable. For this reason, we assembled short reads sequenced by RNA-Seq and compared them with enzymes of related plants to find homologous sequences. We first collected the corresponding sequences in model species (*Arabidopsis thaliana*, *Oryza sativa japonica*, *Glycine max*, and *Zea mays*) from the following databases: Kyoto Encyclopedia of Genes and Genomes (KEGG; http://www.genome.jp/kegg/; Kanehisa et al. 2000); the NCBI Reference Sequence Database (RefSeq; http://www.ncbi.nlm.nih.gov/refseq/; Pruitt et al. 2014); and KNApSAcK Motorcycle (http://kanaya.naist.jp/KNApSAcK\_Family/; Afendi et al. 2012, Ikeda et al. 2013). We also obtained the gene sequences for DCS, CURS1, CURS2, and CURS3 of *C. longa* (Katsuyama et al. 2009b). By comparing these libraries with the assembled scaffolds, we selected 171 scaffolds that were highly homologous to these library genes **[Fig. 3.2**, Step 3**]**. Note that all the scaffolds that were similar to CUS library sequences were more similar to the reference sequences of CURS1–3 and DCS. We therefore did not include CUS (reported in *O. sativa* and others). as a reference. We referred to the selected scaffolds as the reference sequence set of the enzymes for curcuminoid biosynthesis. Each raw read of the four specimens was mapped to the references to count the number of assigned reads **[Fig. 3.2**, Step 4**]**. Finally, to estimate the expression level of each gene, the number of fragments per kilobase of exon per million fragments was computed using the method proposed by Li and Dewey (2011) **[Fig. 3.2**, Step 5**]**.



**Figure 3.2** Schematic illustration of RNA-seq analysis of the curcuminoid biosynthesis pathway
### **3.3 Result and discussion**

#### *Gene expression level calculation*

When multiple scaffolds were assigned to an identical enzyme gene, we simply added all expression values. The final genes' expression results are showed in **Fig. 3.3A**. In this method, the average CV of the estimated expression level for each enzyme was 1.47, whereas the average over the same enzyme was 2.12 when the raw reads were mapped to the whole scaffold first ( $p = 0.019$  by the paired Mann–Whitney U test). We also validated the quality of expression analysis using the RNA-Seq method by evaluating expression levels of housekeeping genes. We chose scaffolds that are homologous to widely used housekeeping genes: glyceraldehyde 3-phosphate dehydrogenase, ubiquitin, tubulin, and elongation factor 1α (Guénin et al. 2008). We computed their expression levels to confirm that their expression levels do not vary among specimens. The CVs of these housekeeping genes among the four specimens ranged from 8.2% to 32.5%. It is worth noting that using the mapping-first analysis, the CVs of the same genes ranged from 12.8% to 46.2% and thus we could reduce the CVs by focusing on the specific pathways.

#### *Species-specific biosynthesis of curcuminoids*

Based on the expression analysis using the RNA-Seq method, we investigated reactions in the curcuminoid biosynthesis pathways. Curcuminoids are synthesized by Type III polyketide synthases (Katsuyama et al. 2009a) from carboxylic acid CoA ester **[Fig. 3.3A]**. First, feruloyl-CoA is produced from phenylalanine via *p*-coumaroyl-CoA. Next, DCS synthesizes feruloyldiketide-CoA from feruloyl-CoA and malonyl-CoA.



**Figure 3.3** Gene expression profiles of the enzymes in the curcuminoid biosynthesis pathway. (**A**) Expression level of each enzyme. The order of enzymes corresponds to the position in the curcuminoids synthesis pathway. (**B-D**) Significance of expression difference. We compared expression levels of enzyme pairs along with the curcuminoids synthesis pathway. Each bar represents p-value of U test, weather the expression levels of adjacent enzyme pairs such as (PAL, C4H), (C4H, 4CL),  $\cdots$  were equal between specimen sets such as {LN, SK} vs. {AR, OU}, etc. The dashed lines represent thresholds *p*=0.05.

Then, CURS1–3 catalyze the formation of curcumin from feruloyl-CoA and from the feruloyldiketide-CoA (Kita et al. 2008, Katsuyama et al. 2009a). Because these DCS and CURS1–3 can catalyze *p*-coumaroyl-CoA and *p*-coumaroyldiketide-CoA, other curcuminoids i.e. demethoxycurcumin and bisdemethoxycurcumin are also produced. On the other hand, another enzyme that synthesizes bisdemethoxycurcumin directly from two *p*-coumaroyl-CoAs and one malonyl-CoA has been reported (Morita et al. 2010). Thus, the content of curcuminoids in these cultivars depends on the balance of these enzymes and the amounts in individual substrate pools.

In the GC-MS analysis, LN and SK contained large amounts of curcumin, less demethoxy curcumin, and little bisdemethoxy curcumin, while OU and AR contained large amounts of demethoxy curcumin, less curcumin, and little bisdemethoxy curcumin **[Fig. 3.4A]**. It is interesting that demethoxy curcumin is the highest curcuminoid in OU. To compare their expression profiles, we divided the four specimens into two groups according to their curcumin content: Group I comprising {LN and SK} (in which curcumin was the largest component) and Group II comprising {OU and AR} (in which demethoxy curcumin was the largest component). We selected all adjacent enzyme sets along the metabolic pathways from 2-gene to 10-gene sets (described in Statistical tests in Materials and Methods), and compared their expression levels between Group I and II using the Mann–Whitney U test. We found that the expression levels of the enzyme pair (CURS1, CURS2) were significantly higher in Group I ( $p = 0.03$ ), and those of the pair (OMT, DCS) were higher in Group II ( $p = 0.06$ ) **[Fig. 3.3B]**. When we compared other specimen pairs—namely, {LN, AR} vs. {SK, OU} and {LN, OU} vs. {AR, SK}, differences in any enzyme sets between them were not statistically significant **[Fig. 3.3C, 3.3D**. It is also worth noting that the expression levels of CURS3 were low in all four specimens.



**Figure 3.4** Curcuminoid biosynthesis pathway. (A) The pathway from phenylalanine to curcuminoids. The relative contents depicted in the bar graphs for curcumin, demethoxycurcumin, and bisdemethoxy curcumin, respectively, are 77.4%, 20.2%, and 2.4% for CL; 50.9%, 35.8%, and 13.3% for SK; 35.1%, 57.2%, and 7.7% for OU; and 20.4%, 78.8%, and 0.8% for AR. The error bars show the standard deviation of three.

The estimated behavior of curcuminoid pathways of Groups I and II can be summarized as shown in **Figs 3.5A** and **3.5B**, respectively. First, in Group I, the low expression of DCS results in the accumulation of feruloyl-CoA (shown in the large blue boxes in the left-side pathways), and then a high expression level of CURS1 and CURS2 (bright red arrows) explains the high curcumin content. Both CURS1 and CURS2 can also catalyze the synthesis of demethoxy curcumin, but they require the respective substrates feruloyl-CoA and *p*-coumaroyldiketide-CoA. When the concentration of *p*-coumaroyldiketide-CoA is low, the production of demethoxy curcumin is restricted. On the other hand, in Group II, because DCS is highly expressed, the flux from *p*-coumaroyl-CoA to *p*-coumaroyldiketide-CoA (thick red arrow) is larger than that to feruloyl-CoA, producing more demethoxy curcumin than curcumin. Because the syntheses of curcumin and demethoxy curcumin are catalyzed by the same enzymes, the difference in curcuminoid contents could be attributed to the difference in their substrate concentrations. To evaluate their concentrations, we measured the amount of coumarate and ferulate instead of *p*-coumaroyl-CoA and feruloyl-CoA and compared their concentration ratio between the four specimens. The ratios of the concentration of ferulate to that of coumarate in LN, SK, OU, and AR were 3.00, 2.80, 2.20, and 2.15, respectively. The differences in these ratios are consistent with the curcumin contents.

Based on the estimated expression levels, we compared the similarities of expression profiles by hierarchical clustering **[Fig. 3.6]**. The results showed that the expression patterns of LN and SK were the closest and OU was the most distant which is consistent with the fact that statistically significant expression difference was obtained in the pathways of pairs of genes OMT and DCS, and CURS1 and CURS2 in two groups {LN, SK} and {AR, OU}. Some *Curcuma* species such as *C. zedoaria* are known to produce high amounts of demethoxy curcumin (Lobo et al. 2009). Moreover, according to the phylogenetic tree estimated from the chloroplast DNA (Záveská et al. 2012), *C. zedoaria* is more distant from *C. longa* than *C. aromatica*. Our results suggest that the phenotype of OU is closer to *C. zedoaria* than to *C. longa*.



**Figure 3.5** Curcuminoids synthesis flux in Group (LN, SK) and Group (OU, AR). Group I comprised LN and SK (in which curcumin was the largest component); Group II comprised OU and AR (in which demethoxycurcumin was the largest component). Bright and dark red arrows represent relative differences in expression levels for DCS vs CURS1 and CURS2. The sizes of the dashed and solid blue boxes show the expected and observed concentrations of the metabolites.



**Figure 3.6** Two-dimensional hierarchical clustering of expression levels. Each row represents a specimen, and each column represents a gene. Depths of color in the green and red rectangles indicate higher and lower expression levels compared with the average, respectively. The dendrograms at the top and the left show the results of hierarchical clustering based on correlation of expression profiles among genes and specimens, respectively. The tree on the left shows that the expression of SK is close to LN while that of OU is far from them, consistently with their curcuminoid contents. The tree on the top shows that the expressions of enzymes adjacent in the pathway were correlated well. The red box of DCS gene shows low activity in LN and SK, but high in AR and OU. The CURS1 and CURS2 show high activity in AR and OU but low in LN and SK. The genes are clustered roughly according to their expression levels. It should be noted that the enzymes for synthesizing *p*-coumaroyl-CoA from cinnamate, C4H and 4CL, were also clustered into the same tree pattern, reflecting the sharing of the same regulatory.

#### *Transcriptome analysis*

For the selection-first analysis, we searched for scaffolds homologous to the amino acid sequences of the enzymes involved in curcuminoid biosynthesis pathways using the BLAST software (http://blast.ncbi.nlm.nih.gov/Blast.cgi; Altschul et al. 1990). The reference amino acid sequences for *A. thaliana*, *O. sativa japonica*, *G. max*, and *Z. mays* were obtained from RefSeq (Pruitt et al. 2014) and KNApSAcK (Afendi et al. 2012, Ikeda et al. 2013). Sequences of curcumin synthases of *C. longa* were obtained from the KEGG database (Kanehisa et al. 2000, Kanehisa et al. 2014). The scaffolds that matching the reference enzymes best were used as a library in Bowtie (Langmead et al. 2009) to map all transcriptome reads. Finally, RNA-Seq by expectation maximization value (Li and Dewey 2011) was computed using the Trinity utility (Grabherr et al. 2011) to obtain the expression level of each enzyme. For the mapping-first analysis, we mapped all transcriptome reads using Bowtie to all assembled scaffolds, and evaluated expression levels using the Trinity utility.

#### *Statistical tests*

To compare expression levels between specimens, we examined two sets of data pairs. First, we compared between the specimens that synthesize mostly curcumin or mostly demethoxy curcumin; namely, between {LN, SK} and {AR, OU}. Next, we also tested on the difference between other specimen groups, i.e. {LN, AR} vs. {SK, OU} and {LN, OU} vs. {AR, SK}. The expression levels of enzymes in a metabolic pathway are often regulated by the same transcriptional factors, so that their expression patterns are correlated (Wei et al. 2006). To detect differences in the expression levels of enzymes in curcuminoid biosynthesis pathways between specimens, we selected several series of genes along the pathway. Here, *g* denotes the index of 10 enzymes ordered along the curcuminoid synthesis pathway (PAL, C4H, 4CL, HCT, C3H, OMT, DCS, CURS1, CURS2, and CURS3), and *Xgh* denotes the expression level of the *g-*th gene of the *h*-th specimen. First, considering that the size of the enzyme set is two  $(l = 2)$ , we

chose pairs of adjacent enzymes  $(g_i, g_{i+1})$ , where  $g_i$  takes 1, ..., 9; namely, the pairs (PAL, C4H), (C4H, 4CL), and so on. Then, we evaluated the difference in the expression levels  $\{X_{gh}\}\$  of genes in the *i*-th set ( $g \in (g_i, g_{i+1})$ ) between specimen groups, (e.g., {LN, SK} vs. {AR, OU}), respectively, by the Mann–Whitney U test. Next, we let  $l = 3$  and chose sets of three contiguous genes  $(g_i, g_{i+1}, g_{i+2})$  from the beginning of the pathway; i.e., (PAL, C4H, 4CL), (C4H, 4CL, HCT), …, and so on. Using these enzyme sets, we compared their expressions between specimen groups. We repeated these processes, increasing the size of the gene sets, until all genes were chosen  $(l = 10)$ .

### **Chapter IV. Conclusions**

We utilized NGS technology on RNA-seq method to reveal the whole genome information of gene expression the cell. The whole genome contains all the secret of a cell. By comparing the gen expression in different samples, we focus on the genes for which the expression level highly changed and then on the whole metabolic pathway related to such genes.

The former part of this research mainly focuses on the major metabolic pathways, which correspond to daily bio-activities of plants. The latter part of the research focuses on the secondary metabolite pathways, which synthesize the metabolic production in a plant. As we discussed in the research, major metabolic pathways are in charge of plant daily activities and provide the substrate for the secondary metabolite synthesis pathway. We also get a preliminary research on how the secondary metabolite pathway genes express in the major pathway analysis. Two cultivars of the turmeric share many common pathways in which a number of the genes are up-regulated in the rhizome. This result indicates high possibility that cucuminoids synthesis mechanisms in these two cultivars are very similar.

We applied an error-resilient, selection-first method for a targeted expression analysis based on RNA-Seq in *Curcuma* species. Although raw reads sequenced by NGS systems may contain substantial noise, we could exploit them through focusing on specific genes and pathways by selecting target sequences of interest *a priori*. In our trial, the method reduced the variance of the estimated expression levels, and reliable

differences were detected for gene expressions in curcuminoid biosynthetic pathways in the four turmeric specimens.

This method is especially effective for plant secondary metabolite biosynthesis where gene expression and metabolite concentration correlate well, and end products accumulate (or, sometimes exuded) without active catabolism. Such secondary metabolite genes are often expressed coordinately, implying that their concerted upregulation increases end-product fluxes (Yonekura-Sakakibara et al. 2013). Yonekura-Sakakibara (2009) also showed that expression of enzymes in flavonoid biosynthesis pathways in *A. thaliana* correlated well with that of key transcription factors. We detected correlation between expression levels of transcription factors and some enzymes in the flavonoid pathways. Our results further corroborate the findings of Mewis et al. (2006) who studied defense-signaling pathways of *A. thaliana* in response to insect feeding. That work showed that contents of glucosinolate often correlate with changes in transcript levels of their biosynthetic genes. Our co-expression analyses indicate that there are similarities in co-regulation mechanisms of enzymes in the same pathway.

Genes associated with identical metabolic pathways are often coexpressed (Ihmels et al. 2003) so that they can catalyze linear chain of reactions. This is evident especially for those involved in secondary metabolic pathways (Gachon et al. 2005, Yonekura-Sakakibara et al. 2007, Aoki et al. 2007; Wada et al., 2011). In this study, we focused on the expression changes of genes adjacent along with the curcuminoid biosynthesis pathway and could classify two groups {LN, SK} and {AR, OU} based on metabolic switch obtained by co-expression of genes and accumulation of metabolites. Secondary metabolic pathways are the most diverse and rapidly evolving features of plant genomes (Wei et al. 2006; Albinsky et al. 2010; Schaefer et al. 2014). Identification of such coexpressed gene sets will provide useful information to regulate production of interesting metabolites. We could estimate changes in their metabolic flux by comparing information on enzymes and their substrates. The results consistently explained differences in curcuminoid contents between the four specimens. Whether genome sequence is available or not, our strategy, namely a targeted integration of RNA-Seq and metabolite data can be applicable to estimate expression regulation of genes in the secondary metabolic pathways of various species.

In this study we combined RNA-seq method based on NGS technique and metabolite analysis together to investigate the plant metabolic pathway. The complexity of metabolite analysis requires not only the assist from genetic aspect but also from metabolite. Though there are plenty of the factors that affect the metabolite pathways, not only the genes and the metabolite, this study is a trial to consider these basic elements.

When we analysze the curcuminoid synthesis pathway, the current whole transciptome analysis method is not very suitable for a small scale synthesis network of genes. All the raw reads map to the whole genome, the information that related the specific genes would be swallowed by the major metabolite pathway information. We developed a "selection-first" method for RNA-Seq analysis in which short reads are mapped to selected enzymes in the target biosynthetic pathways in order to reduce the effect of mapping errors. This strategy lowers coefficients of variation of gene expression level.

We made NGS data mining of both primary metabolic pathways and a specific secondary metabolic pathway. There is relationship between these two kinds of pathway. Primary metabolic pathways have significant meaning to the living creatures for which understanding the mechanism is important. The secondary metabolic pathway also have deep influence on the living creatures.

### **Acknowledgement:**

It is a very important stage of my life to study in Nara Institute of Science as a doctoral student. In the period of my Ph.D study here, I met a lot of people, and learned a lot of knowledge.

I want to thank to my supervisor, Professor Shigehiko Kanaya, who gave me the opportunity to study in the Computational Systems Biology Laboratory. I greatly appreciate his assistance and support during my studies. Professor Kanaya not only gives me the knowledge and the skill during the doctoral study, but also shows me the example of a real scientist.

I would like to thank my thesis committee, Prefessor Shigehiko Kanaya, Professor Keichi Yasumoto, Associate Professor MD.Altafl-Ul-Amin, Associate Professor Tadao Sugihura, Assistant Professor Naoaki Ono. Thank for their valuable comments and supervision of my work. Their valuable advice, guidance, critics mde the dissertation improved greatly.

I would like to thank all the other staff in Computational Systems Biology Laboratory: Assistant Professor Tetsuo Sato, Assistant Professor Alex Ming Huang, Aki H. Morita, Minako Ohashi. It is very kind of you to assist me in daily work and life.

I want to give my great appreciation to Assistance Professor Naoaki Ono, who kindly guided my Ph.D research carefully during all my Ph.D course. And also I want give my appreciation to my friend Katsuragi Tetsuo, and Nelson Nelson Kipchirchir Kibinge, who helped me a lot in my daily research and live.

Last but not least, my appreciation also extends to my parents and my friends. With your understanding, patience, critics, companion, support, and encouragement, I could achieve my doctoral degree.

Thank you very much.

## **List of Publications**

#### **Journal:**

1. Donghan Li, Naoki Ono, Tetsuo Sato,Tadao Sugiura, Md Altaf-Ul-Amin, Daisaku Ohta, Hideyuki Suzuki, Masanori Arita, Ken Tanaka, Zhiqiang Ma, Shigehiko Kanaya; Targeted Integration of RNA-Seq and Metabolite Data to Elucidate Curcuminoid Biosynthesis in Four *Curcuma* Species; Plant and Cell Physiology; 56(5):843-51; 2015 May

#### **International Conference:**

1. Donghan Li, Naoaki Ono, Shigehiko Kanaya, Ken Tanaka; RNA-Seq Analysis of Curcuminoid Synthesis Pathway of *Curcuma Longa*; AMT-BHI 2013 (Active Media Technology, Brain and Health Informatics); 2013 October

2. Donghan Li, Naoaki Ono, Tetsuo Sato, Tadao Sugiura, Md. Ataf-UI-Amin, Masanori Arita, Ken Tanaka, Zhiqiang Ma, Shigehiko Kanaya; Targeted Integration Between RNA-Seq and Metabolomics Data to Elucidate Curcuminoid Biosynthesis Flux in Four *Curcuma* Species; GIW ISCB-ASIA 2014 (The 25th International Conference on Genome Informatic; 2014 December

3. Donghan Li, Naoaki Ono, Tetsuo Sato, Tadao Sugiura, Md. Altaf-Ul-Amin, Masanori Arita, Ken Tanaka, Zhiqiang Ma, Shigehiko Kanaya; Comparison of curcuminoid biosynthesis of Curcuma longa and its cultivars using a pathway based RNA-Seq analysis method; Metabolomics 2015; 2015 July

#### **Domestic Conference:**

1. Donghan Li, Naoaki Ono, Ken Tanaka, Md Altaf-UI-Amin, Tadao Sugiura, Tetsuo Sato, Shigehiko Kanaya; "RNA-Seq Applied on Curcuminoid Synthesis Enzyme Finding"; NGS 現場の会第三回研究会, Kobe, Hyogo, Japan

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# **Appendix**

### **Table 1. Up-regulated genes in leaf in cultivar AR**



























### **Table 2. Up-regulated genes in leaf in cultivar LN**
















































	Scaffold	Annotation	log2(leaf/rhizome)	Pathway
	comp107831 c0	protein MIDASIN1	16.44	Ribosome biogenesis in eukaryotes
2	$compl10162$ c0	Preprotein translocase Sec,	15.94	Protein export; Protein processing in endoplasmic
		Sec61-beta subunit protein		reticulum; Phagosome
3	$compl13126$ c0	APC10; anaphase-promoting	15.01	Ubiquitin mediated proteolysis
		complex subunit 10		
4	comp107761 c1	hypothetical protein	13.56	Taurine and hypotaurine metabolism; Metabolic
				pathways
5.	$compl16992$ c0	Rael-like protein	12.93	RNA transport
6	$compl11085$ c0	RPL27; 50S ribosomal protein	12.84	Ribosome
		L27		
7	$compl14024$ c0	transport protein SEC13A	12.61	RNA transport; Protein processing in
				endoplasmic reticulum
8	$comp120565$ c0	ZAC; ADP-ribosylation factor		Endocytosis
		GTPase-activating protein	12.61	
		AGD <sub>12</sub>		
9	$compl18352$ c0	CHIP; E3 ubiquitin-protein	12.58	Ubiquitin mediated proteolysis; Protein

**Table 3. Up-regulated genes in leaf in cultivar OU**










































metabolites; Biosynthesis of antibiotics; Carbon









## **Table 4. Up-regulated genes in leaf in cultivar SK**































Seq ID	AR	LN	OU	SK	Protein	Pathway
comp121185	10.81	10.49	10.97	9.65	D se I-like superfamily protein	R degradation
$\mathbf{c}$ <sup>0</sup>						
comp120130	10.87	10.85	11.25	11.88	ACX3; acyl-coenzyme A oxidase 3	degradation; Fatty acid alpha-
$\overline{\phantom{0}}$ c <sub>0</sub>						Linolenic acid metabolism;
						Biosynthesis of unsaturated fatty
						acids: Metabolic pathways;
						Biosynthesis of secondary
						metabolites; Fatty acid metabolism;
						Peroxisome
comp103293	11.89	11.52	12.2	14.68	FAB1B; phosphatidylinositol-3P 5-ki Inositol	phosphate metabolism;
$_{\rm c0}$					se-like	Phosphatidylinositol sig ling
						system; Phagosome
comp103986	12.33	13.11	8.71	12.95	EIF2 GAMMA; translation initiation R transport	
$_{\rm c0}$					factor eIF-2 gamma subunit	
comp49043	12.49	12.21	12.2	11.82	$DP-ME2$ ; DP-dependent	malic Pyruvate metabolism; Carbon
c <sub>0</sub>					enzyme 2	fixation photosynthetic in
						Metabolic pathways; organisms;

**Table 5. Up-regulated genes in rhizome of 4 cultivars**

						Carbon metabolism
comp106512	13.91	13.07	8.91	12.97	40S ribosomal protein S16-1	Ribosome
$\sim 0$						
comp110408	13.95	13.4	9.84	9.21	VPS60.2; vacuolar protein sorting	Endocytosis
$_{\rm c0}$					protein 60.2	
comp102333	14.12	12.24	9.5	10.21	RD19; cysteine protei se RD19a	Plant-pathogen interaction
$_{\rm c0}$						
comp107761	14.13	13.49	13.56	14.26	hypothetical protein	Taurine hypotaurine and
$\lfloor c_1 \rfloor$						metabolism; Metabolic pathways
comp113126	14.71	14.34	15.01	12.03	APC10; a phase-promoting complex Ubiquitin mediated proteolysis	
$\overline{\phantom{a}}^{\phantom{0}}$					subunit 10	
comp114089	15.28	15	9.53	14.81	E3 ubiquitin-protein ligase SI T3	Ubiquitin mediated proteolysis
$-c0$						
comp110162	15.84	15.6	15.94	12.88	Preprotein translocase Sec, Sec61-beta Protein export; Protein processing in	
$\sim 0$					subunit protein	endoplasmic reticulum; Phagosome
comp107831	15.96	15.25	16.44	13.76	protein MIDASIN1	Ribosome biogenesis in eukaryotes
$_{c0}$						
comp106412		9.73	9	10.75	Bet1-like protein	interactions RE in vesicular S
$\mathbf{C}^0$						transport
comp123838		9.76	9.36	9.8	RCI3; peroxidase 3	Phenylpropanoid biosynthesis;

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		Metabolic organisms; pathways;
		of Biosynthesis secondary
		Biosynthesis metabolites; of
		antibiotics; Carbon metabolism;
		Biosynthesis of amino acids
9.86	RGA1; DELLA protein RGA	Plant hormone sig 1 transduction
9.92		biosynthesis;
	5	Metabolic pathways; Biosynthesis
		of secondary metabolites
9.95	vesicle <b>SEC22:</b>	transport protein S RE interactions in vesicular
	SEC <sub>22</sub>	transport; Phagosome
9.95	ATDAD1: dolichyl-	N-Glycan biosynthesis; Metabolic
	diphosphooligosaccharide--protein	pathways; Protein processing in
	glycosyltransferase subunit DAD1	endoplasmic reticulum
9.96	QPT; quinoli	te Nicoti and nicoti mide te
	phoshoribosyltransferase	metabolism; Metabolic pathways
9.99		
	family protein	
9.99		phosphorylation;
		CAD5; cin myl alcohol dehydroge se Phenylpropanoid R -binding (RRM/RBD/RNP motifs) Spliceosome VHA-C3; vacuolar-type $H(+)$ -ATPase Oxidative

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$\mathbf{C}^1$			
comp116950	10.04	MEE58; adenosylhomocystei se 1	methionine Cysteine and
$\mathbf{c}$ <sup>0</sup>			metabolism; Metabolic pathways
comp107138	10.06	$CLAI$ : 1-deoxy-D-xylulose-5-	Thiamine metabolism; Terpenoid
$_{\rm c0}$		phosphate synthase	backbone biosynthesis; Metabolic
			Biosynthesis of pathways;
			secondary metabolites; Biosynthesis
			of antibiotics
comp97467	10.09	ALDH3I1; aldehyde dehydroge se 3I1	Glycolysis Gluconeogenesis; $\sqrt{2}$
c <sub>0</sub>			Pentose glucuro and te
			interconversions; Ascorbate and
			aldarate metabolism; Fatty acid
			degradation; Valine, leucine and
			isoleucine degradation; Lysine
			degradation; Arginine and proline
			metabolism; Histidine metabolism;
			metabolism; Tryptophan beta-
			Alanine metabolism; Glycerolipid
			metabolism; Pyruvate metabolism;
			Limonene and pinene degradation;

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$\mathbf{C}^0$			
comp118330	10.9	ATPD: F-type	H <sup>+</sup> -transporting Oxidative phosphorylation;
$\mathbf{C}^0$		ATPase subunit delta	Photosynthesis; Metabolic pathways
comp136955	10.91	PGP6; ABC transporter B family ABC transporters	
$\mathbf{C}^0$		member 6	
comp125633	10.98	peroxidase 52	Phenylpropanoid biosynthesis;
$\mathbf{C}^1$			Metabolic pathways; Biosynthesis
			of secondary metabolites
comp107974	11.08	CUL1; cullin 1	Ubiquitin mediated proteolysis;
$\mathbf{C}^0$			Protein processing in endoplasmic
			reticulum
comp112385	11.11	arginine/serine-rich protein splicing Spliceosome	
$\mathbf{C}^0$		factor 31A	
comp127499 11.12		OVA4; protein ovule abortion 4	Aminoacyl-tR biosynthesis
$_{\rm c0}$			
comp125735	11.19	GLCAK; glucuronoki se G	glucuro Pentose and te
$\mathbf{C}^0$			interconversions; Ascorbate and
			aldarate metabolism; Amino sugar
			and nucleotide sugar metabolism;
			Metabolic pathways

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