Running title: regulatory networks for tomato organ development

Comprehensive regulatory networks for tomato organ development based on the

genome and RNAome of microTom tomato

Jia-Yu Xue[1,#], Hai-Yun Fan[1,#], Zhen Zeng[2,#], Yu-Han Zhou[1], Shuai-Ya Hu[1], Sai-Xi Li[2],

Ying-Juan Cheng[1], Xiang-Ru Meng[1], Fei Chen[3,4,*], Zhu-Qing Shao[2,*], Yves Van de

Peer[1,5,6,*]

[1]College of Horticulture, Academy for Advanced Interdisciplinary Studies, Nanjing

Agricultural University, Nanjing 210095, China

[2]State Key Laboratory of Pharmaceutical Biotechnology, School of Life Sciences,

Nanjing University, Nanjing, 210023, China

[3]College of Tropical Crops, Sanya Nanfan Research Institute, Hainan University,

Haikou 570228, China

[4]Hainan Yazhou Bay Seed Laboratory, Sanya 572025, China

[5]Department of Plant Biotechnology and Bioinformatics, Ghent University,

VIB-UGent Center for Plant Systems Biology, B-9052 Ghent, Belgium

[6]Department of Biochemistry, Genetics and Microbiology, University of Pretoria,

Pretoria 0028, South Africa

[#]These authors contributed equally to this work.

*To whom correspondence should be addressed: yvpee@psb.vib-ugent.be (Y.V.d.P.),

zhuqingshao@nju.edu.cn (Z.Q.S) or feichen@hainanu.edu.cn (F.C.).

Abstract:

MicroTom tomato has a short growth cycle and high transformation efficiency, and is

a prospective model plant for studying organ development, metabolism, and

plant-microbe interactions. Here, with a newly assembled reference genome for this

tomato cultivar and abundant RNA-seq data derived from tissues of different

organs/developmental stages/treatments, we constructed multiple gene

co-expression networks, which will provide valuable clues for the identification of

important genes involved in diverse regulatory pathways during plant growth, e.g.,

arbuscular mycorrhizal symbiosis and fruit development. Additionally, non-coding

RNAs, including miRNAs, lncRNAs and circRNAs were also identified, together with

their potential targets. Interacting networks between different types of non-coding

RNAs (miRNA-lncRNA), and non-coding RNAs and genes (miRNA-mRNA and

lncRNA-mRNA) were constructed as well. Our results and data will provide valuable

information for the study of organ differentiation and development of this important

fruit. Lastly, we established a database (http://eplant.njau.edu.cn/microTomBase/)

with genomic and transcriptomic data, as well as details of gene co-expression and

interacting networks on microTom, and this database should be of great value to

those who wants to adopt microTom as a model plant for research.

Keywords: microTom genome and RNAome, co-expression, non-coding RNA,

interaction, database

Introduction

Tomato (*Solanum lycopersicum*) is one of the most popular fruits (although usually referred to as a vegetable) in the world. In 2020, its annual worldwide production was estimated at about 186 millions of tons and has been increasing every year (http://www.fao.org/faostat). Tomato is also an emerging model plant system for developmental biology and, in some cases, can be an better option than *Arabidopsis thaliana*, e.g., for studies of fruit development [1,2], metabolism [3-5], plant-pathogen interactions [6,7], and arbuscular mycorrhizal (AM) symbiosis [8,9].

MicroTom is a tomato cultivar and currently a widely applied experimental model plant for lab studies. This cultivar has a smaller size than regular tomato cultivars (e.g., Heinz 1706 and M82), and together with a shorter growth cycle and higher transformation efficiency makes it one of the best choices for a lab model among tomato cultivars. However, a high quality genome has been lacking for this model cultivar, despite the fact that hundreds of tomato cultivars/accessions have been (re-)sequenced already [4,10-12]. Nowadays, developmental biologists rely on the Heinz tomato genome as a reference, whereas functional experiments are mainly performed using microTom as transformation system. Many re-sequencing studies have indicated considerable sequence diversity among cultivar/accession genomes [4,12-14] and the newly developed pan-genome strategy revealed the existence of specific genes only belonging to certain cultivars/accessions [11,15,16]. Such observations suggest that the different genetic background between the reference genome and others might complicate experiments, for instance in cloning target genes, potentially leading to failure of the entire experimental design. Therefore, the availability of a high quality microTom genome was badly needed.

In this study, we provide a high-quality genome of microTom and conducted comparative genomic analysis with the previously published 'Heinz' tomato genome. Additionally, together with large amounts of RNA-seq data sequenced by this study and collected from public databases, we present the RNAome landscape of microTom across different organ/developmental stages/treatments and performed comprehensive analyses of the transcriptome of microTom protein-coding genes,

with respect to (aspects of) gene expression and alternative splicing (AS). With the

reference genome and abundant gene expression data, we constructed

co-expression networks for tomato organ development, which will provide valuable

information for the regulation of organ development in the life cycle. Non-coding

RNAs were also identified by combining different sequence strategies, and their

interaction networks were predicted. Finally, we constructed a database

(microTomBase, http://eplant.njau.edu.cn/microTomBase), available for data

download, online search, and demonstration of analytical results. This database will

be invaluable for researchers who employ the microTom tomato as the lab model

plant.

Results

Assembly of the microTom genome and comparative genomics between microTom

and Heinz

Using a combination of 92.40 Gb Nanopore data and 54.38 Gb Illumina data, we first

obtained a microTom genome assembly of 799 Mb with 60 contigs (contig N50 =

41.37 Mb). Then, using the genome of Heinz as a reference, 58 microTom contigs

were further merged to 12 corresponding pseudo-chromosomes. Protein-coding

gene annotation of the microTom assembly captures 98.57 % of the embryophyta

BUSCO (odb10) genes, with 97.89 % single copy genes and 0.68% of duplicates.

These results indicate that our assembled microTom genome has reached a high

standard of quality and completeness (**Table 1**).

With the assistance of three full-length transcriptome RNA-seq, 12 ribo-minus

RNA-seq data, and 69 poly-A enriched RNA-seq datasets derived from different

organs/tissues under different developmental stages and/or treatments (See

Methods and Materials) from this and previous studies [3,17], 35,213 protein-coding

genes were annotated in microTom. Among those, 31,891 genes (90.57%) received

transcriptomic data support from at least one RNA-seq sample. Although microTom

has a similar number of protein-coding genes than Heinz's (34,690), these two

cultivars share only 2/3 one-to-one orthologous genes according to synteny analysis

and bi-directional blast (**Figure 1a**), yet each cultivar encodes thousands of specific

genes, comprising real specific genes, paralogs by duplications, and genes missed by

annotation (mainly in Heinz probably due to inadequate RNA-seq data)

(**Supplementary Figure S1**). For the two cultivars, 4,449 microTom genes were

"hiding" in the Heinz genome (gene length coverage and DNA sequence identity >

90%), only not annotated; while the corresponding number of Heinz genes not

annotated in microTom dropped to a half. This comparison indicates that adequate

and diverse transcriptomic data are critical to a more comprehensive genome

annotation.

Figure 1. Genome annotation of microTom and comparison with Heinz and other species. **(a)**

Protein-coding gene numbers for Heinz and microTom varieties. Shared one-to-one orthologs in

microTom and Heinz genomes are presented in the cross section of the two tomato cartoon

pictures. **(b)** Proportion of genes with multiple transcripts and genes with different transcript

numbers. **(c)** Categories and frequency of AS events in microTom. IR, intron retention; AA,

alternative adaptor; AD, alternative donor; ES, exon skipping. **(d)** Proportion of genes with

annotated UTRs in microTom (MT), Heinz (HZ), *Arabidopsis thaliana* (AT), and *Oryza sativa* (OS).

(e) Dot plot of annotated UTR lengths in microTom, Heinz, *Arabidopsis thaliana* and *Oryza sativa*.

(f) Detected structural variation events of microTom, compared with Heinz. The minimum size of

insertion, deletion, duplication and contraction is 150 bp, the minimum size of inversion is 1 Kb,

and the minimum size of translocation is 10 Kb.

While alternative splicing (AS) has been widely detected in eukaryotes to

generate functionally divergent transcripts from a common parental gene [18], the

Heinz genome did not provide multi-transcript annotation for protein-coding genes.

By incorporating dozens of RNA-seq datasets from PacBio and Illumina platforms,

14,873 (42.24%) microTom protein-coding genes were identified to have multiple

transcripts (**Figure 1b**), with an average of two transcripts per gene. Among all AS

transcripts, intron retention accounts for the largest proportion (23.57%), followed

by alternative acceptor (18.86%), and alternative donor (11.74%) (**Figure 1c**). The

expression patterns of all transcripts were examined based on the transcriptomic

data (**Supplementary Table S1**). Among the AS transcripts, the majority (> 70%)

showed obvious differential expression in different organs and/or developmental

stages (**Supplementary Table S1**), suggesting that these AS transcripts may be

functionally distinct and regulate organ differentiation and development in a more

prevalent manner than we previously thought.

Due to the large amount of transcriptomic data, more comprehensive

information for the untranslated regions (UTRs) was also available. About 71.28% of

microTom genes have annotated UTRs, showing an obviously higher percentage than

that in Heinz and the rice and genomes (**Figure 1d**), and the medium lengths of 5'

and 3' UTRs are 125 bp and 271 bp, respectively (**Figure 1e**). The annotation of UTRs

should provide useful information for gene regulation and expression studies.

Comparing the genomes of microTom and Heinz, over one million single

nucleotide polymorphism (SNP) sites and 40 thousand insertion-deletions (indels) (<

150 bp) were detected. Additionally, a great number of larger structural variations

were also identified (**Figure 1f**), such as bigger-sized genomic insertions, deletions,

duplications, contractions, translocations, and inversions. These small and large

structural variations indicate genomic divergence between the two tomato cultivars,

which may affect experimental results that demand high accuracy, e.g. SNPs and

indels in the coding regions would greatly affect the design of CRISPR guide RNAs.

Co-expression networks

Co-expression networks underlying the development of organs and response to

stimuli were inferred using transcriptome data derived from 22 different

tissues/organs and at different developmental stages and/or different treatments

(three replicates for each sample). All expressed genes were classified into 123

modules (**Figure 2a**, **Supplementary Figure S2** and **Table S2**), whereby each module

contains genes that share a similar expression pattern, and possibly function in the

same regulatory network, defining and/or regulating a specific phenotype. When a

specific phenotype is defined, the corresponding module can be identified, and the

hub genes, as well as the entire network linked to the phenotype can be extracted.

This way, unknown genes in the pathway can be identified, potentially providing

important clues of targets and gene interactions.

Figure 2. MicroTom co-expression networks established based on 22 transcriptome samples of

different organs/developmental stages/treatments. **(a)** 123 modules and their correlation with

22 phenotypes or molecular processes. **(b)** Module 100 and its network, significantly correlated

with AM symbiosis. Gene names (instead of IDs) indicate that these genes have been functionally

characterized and involved in the AM symbiosis. Threads indicate correlation between genes. **(c)**

Top five enriched KEGG pathways in the early stage of fruit development (10 days after anthesis,

"Fruit10Days" on Figure 2a) in the most correlated Module 62 and 63. **(d)** Top five enriched KEGG

pathways in the fully mature stage of fruit development (55 days after anthesis, "Fruit55Days

(Breaker15) on Figure 2a) in the most correlated Module 17 and 23.

For instance, our results indicate that the AM symbiosis in microTom (Root, low

Pi & AMF) is significantly associated with Module 100 (**Figure 2a** and **2b**,

Supplementary Table S2). It could be noticed that several important genes of known

functions in the AM symbiosis pathway are present, and the majority of them are

even hub genes in the network, including PT4, NSP1, RAD1, RAM1, Exo70I, KIN2, and

two WRI5a orthologous (designated as WRI5a-1 and WRI5a-2). It is well-known that

RAM1, RAD1 and NSP1 are regulators relatively upstream in the AM symbiosis

pathway [19-23], and WRI5a is even considered as a master regulator [24], so they should

have broad associations with other genes in the same pathway. Therefore, this

co-expression result makes good sense, not only in identifying the right (expected)

genes, but likely also in suggesting other critical, potentially even hub, genes. In this

case, other unknown genes in the pathway can also be identified through such

expression association (guilt by association), and co-expression analysis should serve

as an effective means to explore unknown functional genes in pathways.

Tomato is one of the, if not the most important model plant for fruit

development studies. Therefore, we collected transcriptomes derived from fruits of

nine different developing stages (10, 20, 30, 35, 40, 43, 47, 50, 55 days after anthesis

and three replicates each), and observed fruits at different developing stages

showing specific associations with different transcriptional modules (**Figure 2a**). For

instance, fruits of 10 days after anthesis are associated with modules 62 and 63

(**Figure 2a** and **Supplementary Table S2**), the genes of which are functionally

enriched in the categories of "Cell motility", "Organismal Systems", "DNA replication"

and "Transcription factors", suggesting that early development of tomato fruits

mainly involves cell division, cell proliferation, and regulatory network development

of this organ (**Figure 2c**); whereas fruits of 55 days after anthesis are associated with

modules 17 and 23 (**Figure 2a** and **Supplementary Table S2**), the genes of which are

functionally enriched in the categories "Fructose and mannose metabolism", "Base

excision repair", "Mismatch repair" and "Translation factors", suggesting

biosynthesis of metabolites, which mainly seems to occur in fully mature fruits

(**Figure 2d**). These different modules indicate distinct major regulatory priorities at

different developmental stages of tomato fruits.

Diverse non-coding RNAs, their targets and interactions

Non-coding RNAs, including miRNA, lncRNA and circRNA, were comprehensively

annotated using multiple RNA-seq data sets. These datasets were generated from six

development stages/organs of microTom tomato plants (root, stem, leaf, flower,

green fruit and red fruit), and under phosphorus deficiency and AM symbiosis status.

A total of 210 miRNAs were identified from the sRNA datasets, of which 164 belong

to 48 known tomato miRNA families in miRBase (**Figure 3a**). We identified 19 tomato

miRNA families previously documented in the miRBase with increased family sizes,

with one to seven more members discovered for each family. Notably, five miRNA

families that have not been documented in tomato (only documented in other plants)

were identified in this study, namely miR157, miR1446, miR1886, miR2111 and

miR3627. Additionally, 46 novel miRNAs were identified (**Figure 3a**). The lengths of

microTom miRNAs range from 20-nt to 24-nt, with 21-nt miRNAs occupying the

largest proportion. Expression analysis revealed that most of the identified miRNAs

were organ-/developmental stage-specific or were only expressed upon stimulation

by Pi deficiency and/or AM symbiosis. Only a few of them could be detected in

multiple samples, e.g. miR403-3p, miR9472-5p and miR166a/g.

Figure 3. **Non-coding RNAs and interaction networks in microTom genome. (a)** Identification of

the microTom miRNAs. The right panel represents known miRNA families and their members

identified in this study and their expression, and the left panel represents novel miRNA families.

The circle heatmap shows miRNA expression (outer to inner): 1. in roots symbiotic with AM fungi

for six weeks under low phosphorus condition, 2. roots without AM fungi under low phosphorus

condition, 3. red fruits, 4. green fruits, 5. flowers, 6. leaves, 7. stems, and 8. roots under normal

phosphorus condition. The histogram represents the new members identified in the known

miRNA families in microTom, the red part is the newly discovered members, and the blue part

indicates the existing members of miRBase. The hexagon represents miRNA families previously

not identified in tomatoes but identified in other plants. **(b)** Proportion of four different types of

lncRNAs. **(c)** An integrated interaction network between miRNAs, lncRNAs and mRNAs. The

purple line in the flow chart represents miRNA target gene prediction using psTargetscan, and the

orange line represents spearman analysis. The green, red and gray dots represent miRNAs,

lncRNAs and mRNAs, respectively. **(d)** The Venn diagram represents the comparison of circRNAs

predicted using three software. **(e)** Distribution of circRNA lengths.

Altogether, 4,835 lncRNAs were annotated from microTom transcripts, and over

2,944 of them (60.89%) were transcribed from intergenic regions, whereas 720, 511

and 210 lncRNAs, were transcribed from the genomic regions overlapping with

protein-coding genes at the sense/antisense strand, or from the intronic sequences,

respectively (**Figure 3b**). The length of microTom lncRNAs ranges from 200 to 15,073

nt, with an average length of 986 nt. Similar to miRNAs, the majority of lncRNAs

showed development stages/tissue-specific or stimulus induced expression. To

explore the potential regulatory roles of miRNAs and lncRNAs, pair-wise interaction

analyses were performed for combinations of miRNA-mRNA, miRNA-lncRNA and

lncRNA-mRNA. The results showed that 266 mRNAs and seven lncRNAs could be

predicted as targets of miRNAs with a significant negative expression correlation.

Significant expression correlation was also observed for 8,672 lncRNA-mRNA pairs,

suggesting potential regulatory relationships. Putting these predicted interactions

together, networks integrating miRNAs, lncRNAs, and mRNAs were constructed

(**Figure 3c** and **Supplementary Table S3**), and these networks should serve as a basic

resource for elucidating the regulatory roles of miRNAs and lncRNAs in tomato

development and response to stimuli.

A comprehensive annotation of circRNA was performed by incorporating the

sequencing results from this study and our previous study [17]. A total of 19,840

circRNAs, supported by three independent software tools were identified by

mapping the sequencing reads onto the microTom genome. The lengths of identified

1,428 high-confidence circRNAs ranged from 197 to 27,820 nt, with an average of

1,428 nt.

Construction of microTom genomic and RNA-omic database

To make our microTom genomic data and analytical results conveniently accessible,

we   constructed   a   database   (microTomBase,

http://eplant.njau.edu.cn/microTomBase), providing online search and download

possibilities of our data and results (**Figure 4**). Through gene ID or sequence blast

searches, interesting genes can be found, together with detailed information,

including genomic positions, gene sequence with detailed structure information

(UTRs and CDSs), functional annotation, multi-transcripts and expressional profiles.

Information of non-coding RNAs and their targets as well as interacting networks is

also provided under the 'non-coding RNA' section, which can also be accessed

through blast search. All microTom protein-coding genes are ascribed to 123

co-expression modules and can be found under the "Co-expression" section.

Genome assemblies and annotation files of the microTom tomato are available for

download. The microTom database will facilitate comparative genomics,

transcriptional regulation and functional studies for tomatoes.

Figure 4. **Demonstration of the database MicroTomBase.** (a) Homepage of MicroTomBase and

the main functions, providing service/information of sequence blast, genomic position anchoring,

gene ID search, co-expression modules, non-coding RNAs and data download. **(b)** The BLAST tool

of MicroTomBase. Users can input genomic, PEP, or CDS sequences as the query sequence and

the resulting alignment scores are ranked from high to low. **(c)** The JBrowse tool for visualization

of microTom genomic details, including gene visualization interface and detailed data on

individual genes. **(d)** Detailed information about genes, including protein and CDS sequence, RNA

editing sites, KEGG and GO annotation, gene family, expression profile and co-expression module.

Discussion

Tomato has been playing an increasingly important role as a model plant for studies of fruit development, plant disease resistance, and symbiosis. Despite being the most employed cultivar, and larges amounts and wide diversities of multi-omic data being available, microTom tomato until now lacked a high quality genome. This study fills this gap by providing a high quality microTom genome assembly, obtained by a combination of Nanopore and Illumina sequencing. Moreover, we integrated a diversity of transcriptome data (obtained from both public resources and our own data) to achieve a comprehensive annotation and profound analyses for this genome, reporting more genes, more and longer UTRs, multiple AS transcripts, co-expression networks, non-coding RNAs and their interaction networks, results which should all serve as a great resource for further genetic and functional studies.

AS is considered as a mechanism to generate multiple transcripts with different functions [18], and a number of studies have reported its extensiveness in organismal life cycles, e.g. organ differentiation and development [25,26], disease ontogenesis [27,28] and response to abiotic and biotic stimuli [29-31]. However, the Heinz tomato genome did not provide information for AS. The microTom genome annotation fills this gap by including multiple transcripts generated by AS. Over 40% of microTom genes are alternatively spliced and the majority of AS transcripts shows differential expression under different conditions, suggesting a broad functional role of AS.

Other than the assist at in-depth genome annotation, the large amounts of transcriptomes also provide data for our co-expression network analyses, which classified microTom transcripts into different expressional modules, and accordingly established diverse networks associated with different phenotypes (different organs, developmental stages and treatments). Potential genes with important functions that have not been recognized can thus be identified based on their association and applied for further functional characterization. Therefore, our co-expression networks should provide useful information for a more precise targeting of candidate genes related to specific phenotypes in the tomato life cycle.

Non-coding RNAs are extensively involved in the post-transcriptional regulation

of gene expression through different mechanisms, and play important roles in a

variety of life processes on plant growth and development, stress resistance, and

interaction with pathogenic or beneficial microbes [32,33]. In tomato, high-throughput

sequencing of miRNAs of microTom have been reported [17,34-36], and functional roles

of miRNAs in fruit developmental regulation have been characterized, e.g.,

miRNA156 [37] and miRNA159 [38]. The profiles of lncRNAs and circRNAs of microTom

have also been investigated, but by only a few studies [17,39]. Moreover, these studies

merely focused on non-coding RNAs at certain specific developmental stages or

treatments, while a full picture of tomato non-coding RNAs is still lacking. In this

study, we comprehensively annotated miRNAs, lncRNAs and circRNAs in the

microTom genome by integrating multiple datasets generated from diverse organs,

developmental stages and treatments (**Supplementary Table S3**), and our results

greatly extended the non-coding RNA list of tomato. Furthermore, the expression

profile of non-coding RNAs among different samples indicate that most of the

identified miRNAs and lncRNAs were specifically expressed in different organ- and

developmental stage or under AM symbiosis, suggesting a conditional induction of

these non-coding RNAs. Furthermore, non-coding RNAs can regulate the expression

of protein-coding genes, directly or coordinatively affecting the translation and

homeostasis of mRNAs [40]. By constructing the interaction networks of the microTom

miRNAs, lncRNAs and mRNAs, we uncovered highly complicated regulatory

relationships between non-coding RNAs and their target mRNAs, which provides

novel insights into the post-transcriptional regulation of protein-coding genes in

microTom.

In summary, this study presents a high-quality genome for the microTom tomato,

and a comprehensive annotation for both coding and non-coding genes, including

splice variants and UTRs. Taking advantage of large amounts of transcriptomes, the

gene expression profile and the co-expression networks are constructed, which will

provide clues for the identification of novel genes involved in diverse pathways.

Non-coding RNAs, including miRNAs, lncRNAs and circRNAs, as well as their potential

targets, were identified and interacting networks were constructed, which   will

provide valuable information for future studies dedicated to exploring the
post-transcriptional regulation of plant development by non-coding RNAs. All these
findings suggest diverse and complicated modifications and regulations at the RNA
level. All these results have been integrated into our online resource, which we hope,
could provide an invaluable resource for researchers studying tomatoes and
employing tomato as a model plant.

Materials and methods

Plant material and data sources

Seedlings of the *Solanum lycopersicum* (cv. 'microTom') were grown in plastic pots
filled with a mixture of sterilized sand/gravel (1:1 ratio) in a climate-controlled
growth room with 16 h light at 24°C and 8 h dark at 22°C. Roots, stems, leaves,
flower, immature green fruits, and mature red fruits were collected from plants
grown in nutrient-rich soil for six weeks, and used for RNAome sequencing. Green
and red fruits were classified by color chart "USDA Visual Aid TM-L-1" (USDA,
Agricultural Marketing Service, 1975).

We also downloaded 75 Illumina RNA-seq datasets and two PacBio RNA-seq
datasets involving different tissues/organs and different developmental stages
and/or different treatments from our previous study [17], and a study performed by
others [3]. Twelve microTom tomato proteomic datasets were retrieved from the
PRIDE Archive database (Proteomics identifications database,
https://www.ebi.ac.uk/pride/archive/).

Library construction and sequencing

Fresh leaves of four-week old microTom that were grown in half-strength Murashige
and Skoog basal medium with sucrose and phytagel were collected, and the genomic
DNA was sequenced on the Nanopore platform using a MinION R9 flow cell, and the
Illumina NovaSeq6000 platform with an insert size of 450bp at Benagen (Wuhan,
China).

Fresh tissues of roots, stems, leaves, flower, immature green fruits and mature

red fruits of plants grown in nutrient-rich soil were subjected to total RNA extraction

using TRIzol (Invitrogen, Carlsbad, USA) according to the manufacturer's protocol,

which were used for subsequent RNA sequencing using different strategies. Samples

from each tissue were subjected to construct a ribo-minus RNA library and small

RNA library for RNA sequencing, whereas a mixture of the six samples were used to

construction a PacBio SMRT library and a circular RNA library. The ribo-minus RNA

libraries, small RNA libraries and circular RNA library were sequenced using the

Illumina HiSeq platform at Novogene Co., Ltd. (Tianjin, China), and the PacBio SMRT

library was sequenced using the PacBio Sequel System at Novogene Co., Ltd. (Tianjin,

China).

Genome assembly and assessment

Firstly, the raw Nanopore reads were corrected and assembled into contigs by

NextDenovo-v2.5.0 (https://github.com/Nextomics/NextDenovo) with default

parameters. After that, Nanopore reads were further mapped into primary contigs

by software Minimap2-v2.17 [41] with the parameter '-ax map-ont', followed by

Nextpolish-v1.4.1 [42] to polish contigs. Meanwhile, the Illumina paired-end reads

were processed to remove adaptor and low quality sequences using

Trimmomatic-v0.38 [43]. Then, the clean Illumina short reads were mapped to the

polished contigs using BWA-MEM-v0.7.17 [44] with default parameters, based on three

iterative rounds of polishing with parameters: '--fix all' by Pilon-v1.23 [45] (read length

N50 = 41.37 Mb). Finally, the polished contigs were aligned to the Heinz genome to

form pseudomolecules, by the software RaGOO-v1.1 [46]. Embryophyta BUSCO-v5.4.2

(odb10) [47] was used to evaluate the integrity of the final assembly.

PacBio transcriptome processing

The SMRTlink-v6.0.0 pipeline was applied to PacBio *Iso-seq* raw data. Firstly, the

circular consensus sequence reads (CCSs) were extracted from subreads of BAM files

with parameters: minLength= 300, minZScore= -999, minPasses= 1,

maxDropFraction= 0.8, minPredictedAccuracy= 0.8, minSnr= 4, noPolish= TURE.

Secondly, CCS reads were divided into full-length non-chimeric (FLNC) reads and

non-full-length (nFL) reads, by identifying whether 5⊡ and 3⊡ adapters and the

poly(A) tail were present. Then, we obtained consensus isoforms using the ICE

algorithm from FLNC reads (Iterative Clustering for Error Correction), which were

further polished with nFL reads to get high-quality consensus FLNC reads based on

Quiver (parameters: hq_quiver_min_accuracy 0.99, others with default parameters).

Finally, the nonredundant FLNC reads were obtained by CD-HIT-v4.8.1 [48] with an

identity cutoff of 0.95. We also used the software LoRDEC-v0.9 [49] to correct

mismatch and nucleotide indels in FLNC reads.

Repetitive DNA identification and Genome annotation

We identified the repetitive elements in the microTom genome based on a

combination of *de novo* and homology-based strategies. A *de novo* library was first

built through RepeatModeler-v2.0.1 [50] and LTR_retriever-v2.9.0 [51]. The repeat region

in the genome was further masked by scanning *de novo* repeat library. Next, we used

RepeatMasker-v4.0.9 [52] to classify the repeat sequences using the parameters: -poly

-html -gff -lib -no_is -xsmall.

The combination of *ab initio*, homology-based and RNA-Seq-based annotation

strategy was applied to predict and annotate the protein-coding genes. Firstly, the

masked genome was trained by BRAKER2-v2.1.5 [53] and GeneMark-ET-v4.69 [54] for *ab*

initio gene prediction. Secondly, for finding homologous genes, related species like

Solanum tuberosum (686_v6.1) and *Solanum lycopersicum* Heinz 1706 (691_ITAG4.0),

which downloaded from Phytozome v13, were loaded into GenomeThreader-v1.7.1

[55] with the parameters: -species arabidopsis -gff3out -intermediate. Thirdly, 81

RNA-Seq (**Supplementary Figure S3 and Table S4**) data sets were used to assist the

annotation. These were evaluated by FastQC-v0.11.9 and Trimmomatic-v0.38 [43] to

trim low-quality and adaptor sequences. Then, these high-quality reads were aligned

to the genome by HISAT2-v2.2.1 [56]. We assembled transcripts with StringTie-v2.1.5 [57]

and TransDecoder-v5.5.0 (https://github.com/TransDecoder/TransDecoder). The

PacBio *Iso-seq* was also applied to forecast complete coding sequences (CDS) by

PASA-v2.5.2 pipeline [58]. Finally, the EVidenceModeler-v1.1.1 pipeline was applied to

integrate the above-mentioned prediction strategies [59]. The GTF annotation file,

assembled from the Illumina and PacBio data, was used for identifying AS events

using the AStalavista v3.2 tool [60].

Functional annotation

Several public databases (PFAM, GO and KEGG) were used to map GO terms for

searching functional motifs and domains by InterProScan-v5.50-84.0 [61]. When the

Gene Ontology terms for each gene were obtained, functions of protein-coding

genes in microTom genome were annotated by SWISS-PROT database, only retaining

the best alignment.

Identification of SVs and SNPs between reference genomes

Structural variations (SVs) were identified by genome-wide alignment between the

microTom and Heinz 1706 (ITAG4.0) genomes using MUMandCo-v3.8 [62], which can

detect over 1 kb structural variations in length. We also used the MUMmer

package-v4.0.0 [63] to align these two genomes. The reciprocal best alignments were

found using the delta-filter program. Then, the uniquely aligned fragments were used

to identify single nucleotide polymorphism (SNP) sites and indels with the show-snp

tool.

Gene expression and construction of co-expression networks

The RNA-seq dataset for gene co-expression analysis was obtained from samples

with 22 various tissues/organs and at different developmental stages and/or

different treatments. The normalized expression of RNA-seq data was calculated with

FPKM (fragments per kb per million reads) from all samples. FPKM values lower than

1 were filtered out. We used the R package WGCNA (v1.66) [64] to construct

co-expression networks, and the soft threshold value was calculated by

pickSoftThreshold integrated in WGCNA. We used cytoHubba and MCODE to identify

candidate hub genes, and used Cytoscape-v3.9.1 [65] to visualize the co-expression

networks.

Identification and annotation of Non-coding RNAs

The prediction of protein-coding potential for transcripts generated from Illumina

and SMRT data was conducted by integrating CPC2 v0.1, CNCI v2, PLEK v1.2, and

PFAM v32[66-69]. Candidate lncRNAs were defined as transcripts with the longest

representative sequence lacking any open reading frame (ORF) exceeding 100 amino

acids, while having a minimum nucleotide sequence length of 200 nts. MiRNAs were

identified   using   miRador   (https://github.com/rkweku/miRador)   with   slight

modification [70]. Specifically, the sequences with the highest abundance of each

miRNA locus were added as candidate miRNAs. Candidate miRNAs were annotated

as known or novel miRNAs through referencing the latest miRBase version 22.1 [71].

CIRI2 (v2.0.6), CIRIexplorer2 (v2.4.0), and Find_ciric (v1.2) were combined to detect

potential back-splice sites of candidate circRNAs [72-74]. Reconstruction of full-length

circRNAs was achieved using CIRI-full [75].

Identification of targets of miRNAs/lncRNAs

Potential miRNA targets (mRNAs and lncRNAs) were firstly predicted by using the

psRNATarget   v2   program.   Then,   the   expression   values   of   resultant

miRNA-mRNA/lncRNA pairs for six tissues (roots, stems, leaves, flower, immature

green fruits, and mature red fruits) were subjected to the spearman correlation

coefficient analysis. MiRNA-mRNA/lncRNA pairs were considered to be a candidate

interactional miRNA-target when the spearman correlation coefficient was <-0.80

and the p value was <0.01.

To predict lncRNA-mRNA co-expressed pairs, the spearman correlation analysis

was performed between lncRNAs and mRNAs in 75 RNA-seq samples. For more

accurate prediction of lncRNA-mRNA correlations, we increased the threshold of

spearman correlation coefficient| to >0.9, and the p value <0.01. We also screened

the results that met the above requirements based on six or more samples with

FPKM greater than 1, considering these lncRNA-mRNA pairs to be co-expressed.

Data availability

The data supporting the findings of this work are available within the paper and its Supplementary information files. The datasets generated and analyzed during this study are available from the corresponding author upon request. All sequencing data generated have been deposited in National Genomics Data Center (https://bigd.big.ac.cn/) with BioProject ID: PRJCA012325 under GSA: CRA008482. The genome assembly, along with the gene models, the functional annotation, and some supplementary information files are available on the FigShare at the link: (https://doi.org/10.6084/m9.figshare.21509817). All these information can also be accessed under GWH: WGS029763 and microTomBase (http://eplant.njau.edu.cn/microTomBase).

Author contributions

J.Y.X., Z.Q.S., F.C. and Y.V.d.P. conceived the study. Z.Q.S. and Z.Z. collected plant samples. H.Y.F. conducted genome assembly and annotation. H.Y.F., Z.Z., S.Y.H. Y.J.C., and S.X.L conducted analyses of RNA-seq data. Y.H.Z. constructed the database. J.Y.X. and Z.Q.S. drafted the manuscript. All authors read the manuscript and participated in the revision of the manuscript. All authors approved the final manuscript.

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Conflict of interest statement

Supplementary information

Supplementary Fig. S1. Statistics the number of duplicate genes, specific genes and

missed genes due to annotation in Heinz and microTom.

Supplementary Fig. S2. The expressed transcripts classified into 123 modules.

Supplementary Fig. S3. Information about transcriptome datasets and sequencing

strategies.

Supplementary Fig. S4. Evolutionary and divergence time estimation. Phylogeny of

eleven species. The numbers on the nodes indicated the divergence time of species

(Mya, million years ago), with the confidence range in brackets.

Supplementary Fig. S5. Genomic collinearity analysis between microTom and Heinz.

Supplementary Fig. S6. Density of synonymous substitutions per synonymous site (Ks)

of collinear paralogous genes.

Supplementary Table S1. Quantitative expression of transcriptome data (Fpkm).

Supplementary Table S2. Gene information in the model block.

Supplementary Table S3. A dataset of significantly correlated combinations between

non-coding RNAs and their target RNAs.

Supplementary Table S4. Summary of transcriptome mapping for microTom tissues.

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Table 1. Statistics and comparison of microTom and Heinz genomes

	MicroTom				Heinz 1706 (SL4.0)			
	Contigs		Pseudomolecules		Contigs		Pseudomolecules	
	Size(bp)	Number	Size(bp)	Number	Size(bp)	Number	Size(bp)	Number
N50	41,367,923	8	66,788,879	6	6,007,830	37	65,269,487	6
Maximum length	68,578,620		94,893,795		26,291,688		90,863,682	
Total number	60		12		448		12	
Gaps number	47				435			
Assembled length	798,935,606				782,475,302			
BUSCO completeness	98.57%				97.40%			
Gene models number	35,213				34,690			