

Editorial

Approaches for Disease Resistant Candidate Genes Identification in Plants: Recent Techniques and Trends

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Editorial

Global food supply for the thriving world population is a big challenge. Annual production of economically important crops such as wheat, rice, maize is adversely affected by several diseases caused by various pests and pathogens resulting almost 20-40% yield loss [1]. Hence, to ensure sustainable food security, we need to engineer long-lasting and broad-spectrum disease resistance in crops. Development and utilization of disease-resistant/tolerant cultivars have been considered as one of the most important tools for mitigating diseases in agronomic, horticultural or forestry crops. One of the major objectives of plant research is to improve our understanding on plant immune system and unravel how this is manipulated by pathogens, in order to engineer crops for durable resistance against pathogens [2]. While the identification of Candidate Genes (CGs) involved in defense response remains a challenge, several strategies have been developed in this subject in the last decade. CGs identification approaches can be broadly classified in three groups.

Genetic Approaches

First instance of disease resistance traditional breeding was reported in wheat [3]. However, at that time, traditional breeding programs were used to identify resistant sources in crops by classical methods and introgressing them into economically important crops by crossing without any knowledge about Resistance (*R*) genes and their respective mechanisms. Major breakthrough in the understanding of plant disease resistance as 'gene-for-gene' concept was designed by the work of Flor [4] which defined that an Avirulence (*Avr*) gene in the pathogen and an *R* gene in the host plant are required to mount an immune response in plant. Currently, transgenic approaches are being used to reduce the estimated time on classical breeding by several years to create disease resistant crops [5]. For the successful deployment of disease resistance genes, we need to have handful of resistance gene candidates to create disease resistance cultivars. CGs involved in defense responses can be broadly classified into two groups. The first group is for the genes those are involved in the initial recognition of pest or pathogen, the resistance (*R*) genes and the other group is for the genes those are involved in Defense Response (DR) triggered by the recognition event [6]. CG approach has proven extremely significant for studying the genetic architecture of complex traits including disease resistance. Genetic linkage

analysis (mapping) has been commonly used in plants to screen CGs and subsequently clone these genes for controlling disease resistance/tolerance traits. Genetic maps of markers for genes can assist in choosing positional CGs. This is accomplished by evaluating the closeness of linkage with the trait loci. The CG approach has been used to characterize disease resistance loci. Numerous disease candidate genes involved in pathogen recognition and defense response have been isolated in various crops such as in rice against gall midge insect infestation [7-10]. Linkage analysis involves creating bi-parental populations, genotyping and phenotyping of segregating progeny in the populations, and testing if sequence variations in the CGs co-segregate or co-localize with the loci controlling the disease resistance/tolerance trait in the populations [11]. Association mapping has been widely used in human and animal genetics, and it has emerged as a new approach to screen candidate genes in plants [11,12]. This approach uses existing natural populations and germplasm accessions, collections of cultivars, breeding lines from breeding programs, and statistical analysis to reveal association between sequence variations in candidate genes and phenotypic variations in the association study panels.

Both the approaches have their own advantages and disadvantages [11,13]. Segregating populations need to be constructed for linkage analysis which requires longer time and more resources, but it offers better experimental control of plant materials to be genotyped and phenotyped. On the other hand, association study takes advantage of linkage disequilibrium and historical and evolutionary recombination events, therefore improving the mapping resolution [13]. Since it examines a more diverse pool of germplasm beyond the parents used in linkage analysis, association study may discover additional genes or alleles for the trait of interest. However, the study panels selected for association study are "uncontrolled" populations among the panel members that may cause spurious associations [12]. These two approaches are being widely used complementarily in plants, with one approach to discover candidate genes, and the other to validate the discovery [11].

Genomics Tools

Identifying sequence variations in CGs and determining the genotype of progeny in segregating populations are the most essential steps in linkage or association analysis; yet, for many decades, these steps were the most limiting factors. Thanks to the development of massively parallel target capture/enrichment and next-generation DNA sequencing tools, large-scale sequence variation identification and genotyping are no longer a technical obstacle [14]. Genomic approaches for identification of expressed genes such as Expressed Sequence Tag (EST) using Suppression Subtractive Hybridization (SSH) [15], Serial Analysis of Gene Expression (SAGE) [16] and Massively Parallel Signature Sequencing (MPSS) [17] have been widely used in genome-wide gene expression studies in various organisms.

SAGE and MPSS are two powerful tools for deep transcriptome analysis and have been developed to evaluate the expression patterns of thousands of genes in a quantitative manner without prior sequence information [16,17]. However, complicated cloning procedures involved in the SAGE and MPSS library construction have inhibited a wide use of these two methods in plant species [18]. Among these techniques, SSH has high subtraction efficiency and harbors an equalized representation of differentially expressed sequences which can separate effectively both high and low copy expressed genes mainly because of normalization. EST sequencing was the first method used for rapid identification of expressed genes. In the last several years, many defense related genes have been isolated using Real-time PCR, Affymetrix microarray chips, SSH and cDNA library differential screening methods [19-22]. Among available next-generation sequencing systems, Illumina HiSeq system is currently the most widely used platform in many genome sequencing and re-sequencing projects for its high accuracy, unrivalled output, and superior cost-effectiveness. HiSeq 2000 can generate up to 55 Gb per day from a 2x100 bp run, which enables genome sequencing and genotyping-by-sequencing completed in an unprecedented fashion. The availability of this system has greatly accelerated the discovery of new CGs and allelic variations among susceptible and resistant plant genotypes [23-26].

Next-generation sequencing is used in different ways to address various questions in plant genomics. Whole Exome Sequencing (WES) by high-throughput sequencing of target-enriched genomic DNA (exome-seq) has become common in basic and translational research. Exome sequencing is a capture based method developed to identify variants in the coding region of genes. Exome sequencing has the advantage that oligonucleotide probes (baits) are hybridized to genomic DNA to capture the RNA coding regions and provides better coverage for SNP calling. It is also more economical compared to Whole Genome Sequencing (WGS) allowing analysis of more individuals and populations. However, WGS is more comprehensive and structural variants could be detected in non-coding regions such as promoters regions of disease related CGs. Currently three major exome enrichment platforms are available; NimbleGen's SeqCap (<http://www.nimblegen.com/seqcap/>), Illumina's TruSeq Exome Enrichment (<http://www.illumina.com/techniques/sequencing/>) and Agilent Technologies' SureSelect (<http://www.genomics.agilent.com/>). The first is an array-based, while the other two are solution-based hybridization capture systems. The technologies diverge in their choice of target such as DNA for NimbleGen and Illumina, and RNA for Agilent, bait lengths, bait density and molecule used for capture. These enrichment methods of sequencing have been successfully used to capture and enrich tens of thousands of genes [27]. Nevertheless, SureSelect system needs smaller amounts of input DNA and is easier to multiplex samples and automate sample preparation, which seems to have better specificity and reproducibility [28].

Bioinformatics Approach

In modern world, *in-silico* methods are being used for investigation, establishment, and classification of disease resistant CGs. With the increase in accessible data from numerous plant genomes databases and functional genomics information, methods of identifying CGs are rapidly evolving. Genome databases are now an integral part in the process of candidate disease genes selection.

Merging the positional information of CGs from linkage analysis along with the functional characteristics is the usual approach by which candidate disease genes are selected [8,22]. Among various *in-silico* methods available for CGs identification, one of the most commonly used strategy is meta-analysis where converging output of experimental data from different labs with different experimental conditions are mined using same statistical algorithms. Meta-analysis of microarrays and RNA-Seq has been used extensively in animal systems to define robust, regulated probe sets [29]. Recently, meta-analyses have also been used to identify differentially expressed probe sets in plants [30-32]. The other popular ways for CGs identification are HMM search, gene ontology, comparative genomics, molecular evolution, machine learning and cluster analysis [33]. *In-silico* ways from prioritizing the CGs are done by identification of gene structure variation, orthologs, protein-DNA interactions, and co-expression gene analysis and protein-protein regulatory network. These techniques place the potential disease-causing proteins in a functional context, comparative to other known disease related genes, and thus, systematic investigation of such complexes might unmask new candidate genes.

In conclusion, a manageable list of CGs is essential for direct evaluation of these genes with resistance/susceptibility for a given crop disease. The combination of above mentioned CG identification methods such as association mapping, linkage analysis, next-generation sequencing and *in-silico* analysis yield CGs those are required as the first phase for functional analysis of the genotype-phenotype relationship.

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