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Genome-wide identification and characterization of small RNAs in *Rhodobacter capsulatus* and identification of small RNAs affected by loss of the response regulator CtrA

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ABSTRACT

Small non-coding RNAs (sRNAs) are involved in the control of numerous cellular processes through various regulatory mechanisms, and in the past decade many studies have identified sRNAs in a multitude of bacterial species using RNA sequencing (RNA-seq). Here, we present the first genome-wide analysis of sRNA sequencing data in Rhodobacter capsulatus, a purple nonsulfur photosynthetic alphaproteobacterium. Using a recently developed bioinformatics approach, sRNA-Detect, we detected 422 putative sRNAs from R. capsulatus RNA-seq data. Based on their sequence similarity to sRNAs in a sRNA collection, consisting of published putative sRNAs from 23 additional bacterial species, and RNA databases, the sequences of 124 putative sRNAs were conserved in at least one other bacterial species; and, 19 putative sRNAs were assigned a predicted function. We bioinformatically characterized all putative sRNAs and applied machine learning approaches to calculate the probability of a nucleotide sequence to be a bona fide sRNA. The resulting quantitative model was able to correctly classify 95.2% of sequences in a validation set. We found that putative cis-targets for antisense and partially overlapping sRNAs were enriched with protein-coding genes involved in primary metabolic processes, photosynthesis, compound binding, and with genes forming part of macromolecular complexes. We performed differential expression analysis to compare the wild type strain to a mutant lacking the response regulator CtrA, an important regulator of gene expression in R. capsulatus, and identified 18 putative sRNAs with differing levels in the two strains. Finally, we validated the existence and expression patterns of four novel sRNAs by Northern blot analysis.

Introduction

Bacterial small non-coding RNAs (sRNAs) are regulatory RNAs that are heterogeneous in size (generally approximately 50 to 250 nucleotides) and structure. sRNAs are known to function in a number of regulatory processes such as inhibition and activation of translation, degradation and stabilization of mRNA, transcriptional interference, and control of protein activity. sRNAs are usually classified into five categories based on their regulatory mechanisms. Cis-encoded base-pairing RNAs are those that bind to their mRNA target with the highest degree of complementarity. An example of this type of sRNA is GadY, which is involved in the regulation of the acid response system of Escherichia coli.^{1,2} Riboswitches are cis-regulatory elements that directly bind a metabolite when abundance of this metabolite exceeds a threshold level. This binding induces a conformational change in the RNA to form a structure that affects transcription termination or translation initiation.³ Some riboswitches also function as sRNAs and are able to act in trans, such as the S-adenosylmethionine (SAM) riboswitches SreA and SreB of Listeria monocytogenes.⁴ These two riboswitches regulate the expression of the virulence regulator PrfA by pairing with the 5' untranslated region (UTR) of its mRNA.⁴ Trans-encoded base-pairing small RNAs have limited complementarity to their target mRNA(s) and can, in some cases, regulate more than one target. A well-characterized example of a trans-encoded regulatory sRNA is RyhB, which is involved in the regulation of intracellular iron usage in bacteria such as *E. coli*.⁵ Protein modulator sRNAs are ones that counter the activities of mRNA-binding proteins. An example is CsrB, which is part of the carbon storage regulator (Csr) system in E. coli.⁶ The final category consists of the clustered regularly interspaced short palindromic repeat (CRISPR) RNAs (crRNAs), which are palindromes interspaced with short unique spacer sequences that act as a defense mechanism against homologous foreign DNA, such as that from viruses.⁷

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Numerous cellular processes, such as metabolic reactions, quorum sensing, biofilm formation, stress responses, and pathogenesis, are controlled by sRNAs in various species of bacteria.8 In the last decade, high-throughput RNA sequencing (RNA-seq) methods have been employed to identify sRNAs on a genome-wide scale in numerous bacterial species (see Table 1 for some examples). In this work, we used sRNA-Detect⁹ to perform the first genome-wide detection of sRNAs from RNAseq data in the purple nonsulfur alphaproteobacterium Rhodobacter capsulatus. This is an organism of interest for its metabolic versatility¹⁰ and production of a gene transfer agent.¹¹ We performed comparative RNA-seq targeting sRNAs in the R. capsulatus wild type strain, SB1003, and a mutant strain, SBRM1, lacking the histidyl-aspartyl phosphorelay response regulator CtrA, and identified 422 putative sRNAs expressed in R. capsulatus in the early stationary growth phase when growing in photoheterotrophic conditions. Among these 422 putative sRNAs, we identified 18 sRNAs with differing levels in the two strains. Based on significant matches to sequences in the Rfam database,¹² in the RNAcentral database,¹³ and in the bacterial small regulatory RNA database (BSRD),¹⁴ 19 of the 422 putative sRNAs were assigned a predicted function. The transcript levels for selected sRNA candidates were validated by Northern blot analysis.

We also collected genome sequences and published putative sRNAs from 23 additional bacterial species, which included representatives from the phyla *Chlamydiae, Firmicutes*, and *Actinobacteria*, and the *Alpha-, Beta-, Gamma-, and Epsilon-proteobacteria* classes of the phylum *Proteobacteria*. This yielded a collection of 4,725 predicted sRNAs. Based on sequence comparisons, 124 of the 422 putative *R. capsulatus* sRNAs were conserved in at least one other bacterial species.

Finally, we characterized all putative sRNAs for four bioinformatics characteristics and then applied machine learning

 Table 1. List of bacterial species and sRNAs used for comparative analysis.

approaches to develop a quantitative model to calculate the probability of a given RNA sequence to be a bona fide sRNA. The model was able to correctly classify 95.2% of sequences in a validation set.

Results and discussion

Sequencing and detection of R. capsulatus sRNAs

We grew cultures under photoheterotrophic conditions to early in the stationary phase of growth so that the data collected would match with our most comprehensive collection of transcriptomic data from previous microarray studies.^{15,16} Sequencing of sizeselected RNA, ≤ 200 nucleotides, from the genome-sequenced strain, SB1003, and its derived *ctrA* mutant strain, SBRM1,¹⁷ generated a total of 4.45 million reads. From these reads, 93.5% were uniquely mapped to the *R. capsulatus* genome. These sequence data have been submitted to the NCBI Gene Expression Omnibus (GEO) under accession number GSE82056.

Recently, we showed that sRNA-Detect, a new computational program for the detection of bacterial small transcripts from RNA-seq data, exhibits higher recall rates at comparable specificity levels than other standalone computational approaches.⁹ We used sRNA-Detect on our sequence data, and after removal of detected small transcripts located within annotated tRNAs (tRNAs) and rRNAs (rRNAs), we detected 422 potential sRNAs in *R. capsulatus*.

sRNAs with predicted functions or homologs

To annotate *R. capsulatus* putative sRNAs with predicted functions, we retrieved significant matches to *R. capsulatus* sRNAs from the Rfam, RNAcentral and BSRD databases. Based on these matches, we annotated 19 sRNAs with predicted functions (Tables 2 and S1). There were six riboswitches (including

Species	Phylum or class	Genome assembly accession number	Number of sRNAs	Reference
Chlamydia trachomatis L2b/UCH-1/proctitis	Chlamydiae	NC 010280.2	46	52
Clostridium difficile 630	Firmicutes	NC_009089.1	253	53
Streptococcus pneumoniae TIGR4	Firmicutes	NC_003028.3	88	54
Bacillus subtilis subsp. subtilis str. 168	Firmicutes	NC_000964.3	84	55
Corynebacterium qlutamicum ATCC 13032	Actinobacteria	NC_003450.3	805	56
Mycobacterium tuberculosis H37Rv	Actinobacteria	NC_000962.3	258	57
Propionibacterium acnes KPA171202	Actinobacteria	AE017283.1	79	58
Streptomyces venezuelae ATCC 10712	Actinobacteria	NC_018750.1	175	59
Streptomyces avermitilis MA-4680	Actinobacteria	NC_003155.4	199	59
Streptomyces coelicolor A3	Actinobacteria	NC_003888.3	92	59
Campylobacter jejuni RM1221, 81–176, 81116, and NCTC11168	Epsilonproteobacteria	NC_003912.7, NC_008787.1, NC_009839.1, NC_002163.1	102	60
Helicobacter pylori 26695	Epsilonproteobacteria	NC_000915.1	276	61
Neisseria gonorrhoeae FA 1090	Betaproteobacteria	NC_002946.2	231	62
Caulobacter crescentus sp K31	Alphaproteobacteria	NC_010338.1	29	34
Rhodobacter capsulatus SB1003	Alphaproteobacteria	NC_014034.1 NC_014035.1	422	This work
Aarobacterium tumefaciens	Alphaproteobacteria	NC 003062.2, NC 003063.2	187	63
Rhodobacter sphaeroides 2.4.1	Alphaproteobacteria	NC_007493.2, NC_007494.2	28	19,64
Sinorhizobium meliloti 1021	Alphaproteobacteria	NC 003047.1	150	65
Vibrio cholerae O1 biovar El Tor str. N16961	Gammaproteobacteria	NC 002505.1, NC 002506.1	480	66
Pseudomonas aeruginosa UCBPP-PA14	Gammaproteobacteria	NC 008463.1	165	67
Escherichia coli str. K-12 substr. MG1655	, Gammaproteobacteria	NC_000913.2	309	68
Erwinia amylovora ATCC 49946	, Gammaproteobacteria	NC_013971.1	40	69
Yersinia pestis KIM10+	Gammaproteobacteria	NC_004088.1	31	70
Salmonella enterica subsp enterica serovar Typhimurium str. SL1344	Gammaproteobacteria	NC_016810.1	113	71

Table 2. List of functionally annotated sRNAs.

ldentifier(s)	Inferred Annotation
sRNA00627	TPP riboswitch
sRNA00822	Signal recognition particle (SRP) RNA (ffs)
sRNA00687, sRNA00526, sRNA00688, sRNA00508, sRNA01035	Cobalamin riboswitch
sRNA00123	lpha-operon ribosome binding site
sRNA00598	Bacterial small signal recognition particle RNA
sRNA01208	cspA thermoregulator
sRNA01158, sRNA01157, sRNA01156	Transfer-messenger mRNA (fragment of)
sRNA01077	Upstream sRNA of mraZ, UpsM
sRNA00648	6S RNA
sRNA00470	Homologous sRNA to the <i>Rhodobacter</i> sphaeroides validated sRNA RSs1386
sRNA01141, sRNA01140, sRNA01139	Ribonuclease P catalytic RNA (fragment of)

those binding thiamine pyrophosphate and cobalamin), three segments of transfer-mRNA (tmRNA), three segments of the catalytic RNA of ribonuclease P (RNase P RNA), the signal recognition particle (SRP) RNA (ffs), 6S RNA, an α -operon ribosome binding site, the *cspA* thermoregulator, the upstream sRNA of *mraZ* (UpsM)¹⁸ and an sRNA homologous to a validated *Rhodobacter sphaeroides* sRNA (RSs1386).¹⁹ Several sRNAs corresponding to fragments of the tmRNA and the RNase P RNA were predicted due to differences in read depth coverage across the full length of these transcripts.

To investigate the extent of sequence conservation of putative R. capsulatus sRNAs in different bacterial species, we obtained sRNA sequences identified in recent studies of 23 other bacterial species (Table 1) and used BLAST (version $(2.2.30+)^{20}$ to search for pairwise reciprocal best matches between the sRNAs of each of the other 23 bacterial species and the R. capsulatus sRNAs from this study. As differences in the characteristics of each study, including but not limited to differences in sequencing platforms, growth conditions, RNA extraction methods, and sRNA identification methods, lead to limitations in this analysis, we also searched for sequence conservation of R. capsulatus sRNAs in the genomes of these 23 other bacterial species. In total 124 (or 29%) of the 422 putative sRNAs had homologous sRNAs or were found to be conserved in the genome of at least one other bacterial species (Fig. 1). We organized these 124 sRNAs based on our level of confidence in their conservation. We referred to sRNAs with matches in at least one of the three RNA databases (Rfam, RNAcentral and BSRD) as hypothetical equivalogs, which represented 24 sRNAs that likely belong to a set of sRNAs conserved with respect to function. This category includes the 19 sRNAs for which we inferred a function. We classified sRNAs with homologs found in bacterial species belonging to other genera as inter-taxa homologs, which represented 40 sRNAs that are likely to be true functional sRNAs. The sRNAs whose sequences were only present in the genome of the related bacterial species R. sphaeroides were classified as intra-genus homologs, which represented 60 sRNAs. The remaining 298 putative R. capsulatus sRNAs appear to be species-specific. Not surprisingly, there are more intra-genus than inter-taxa homologs and, as already pointed out by Gomez-Lozano et al.,²¹ there is limited sRNA sequence conservation across different species.



Figure 1. Map of 124 sRNAs in *R. capsulatus* with sequence conservation in other bacterial species. Sequence similarity searches were performed for all putative *R. capsulatus* sRNAs against three RNA databases and a panel of 23 bacterial species including representatives from the *Chlamydiae, Firmicutes*, and *Actinobacteria* phyla and the *Alpha-, Beta-, Gamma-, and Epsilonproteobacteria* classes of the phylum *Proteobacteria*. From right to left, three classes (hypothetical equivalogs, 24 sRNAs; inter-taxa homologs, 40 sRNAs; and intra-genus homologs, 60 sRNAs) proceed from nearly complete certainty about a putative sRNA's function to no functional information. Gray indicates no homologs (matches) were found for the sRNA in that organism or database.

Bioinformatic characterization of putative sRNAs in R. capsulatus

We characterized all 422 putative sRNAs in terms of their predicted secondary structures, their proximities to predicted promoter sites, their proximities to predicted Rho-independent terminators, and their genomic contexts. To be able to compare the features of the putative sRNAs with a null distribution, we randomly extracted sequences matching the length and strand of putative sRNAs from the R. capsulatus genome. There were at least 10 random sequences for each putative sRNA sequence. We used CentroidFold²² to predict the secondary structures of both the sRNA sequences and the random sequences, and to calculate the free energies of the folded structures. We found that the distribution of free energies of the sRNAs' secondary structures was shifted toward lower values than the distribution of free energies of the random sequences' secondary structures (Fig. 2A). The difference between the free energies of the sRNAs' secondary structures and the free energies of the random sequences' secondary structures was statistically significant (p = 5.9E-12, Mann-Whitney test). This indicates that our putative sRNAs tend to adopt more stable conformations than random genomic sequences.

Using the BPROM program,²³ we searched for putative promoters in the region spanning 150 nucleotides (nts) upstream to 20 nts downstream from the predicted 5' ends of both the putative sRNAs and the random genomic sequences. Of the 422 putative sRNAs, 183 (43%) had predicted promoter sites, in contrast to 18.6% of the random sequences. Furthermore, there was a distinct peak at position -21.5 in the probability density function for the -10 promoter positions of putative



Figure 2. Characteristics of putative sRNAs in comparison with the null distribution. (A) Probability distribution of the free energy of the predicted secondary structures for the putative sRNAs (red line) and 4,400 random genomic sequences of matching length and orientation (black line). The average free energy of the sRNAs' predicted secondary structures is statistically significantly lower than the average free energy of the random sequences' secondary structures (p = 5.902E-12, Mann-Whitney test). (B) Density function of the number of nucleotides (nts) upstream from the predicted 5' end of the putative sRNAs to -10 (solid red line) and -35 (dashed red line) predicted promoter sites in comparison with the number of nts from the 5' end of random genomic sequences to -10 predicted promoter sites (solid black line). (C) As B, but number of nts downstream from the predicted 3' end of the putative sRNAs (red line) to predicted Rho-independent terminators. (D) Proportion of sRNAs (left) and random genomic sequences (right) in a specific class of genomic context (antisense (AS), 28 sRNAs; intergenic (I), 150 sRNAs; partial overlapping on both ends (POb), 46 sRNAs; and sense (S), 12 sRNAs).

sRNAs, whereas the random sequences had a uniform probability distribution for the -10 promoter positions (Fig. 2B). As sRNA-Detect tends to predict transcripts that lie within the boundaries of the actual sRNA (i.e., it misses some nucleotides at the 5' and 3' ends of the sRNAs),⁹ the average distance to the -10 and -35 promoter sites from the actual 5' end of the sRNAs would be less than as estimated above. Our data



Figure 3. Schematic illustration of the different classes of genomic contexts of sRNAs. Genes are depicted as thick arrows with open reading frames (ORFs) shown in gray and sRNAs shown in red. Only a subset of all possible direction of transcription combinations are shown. Antisense RNAs (asRNAs) are within an ORF that is transcribed on the strand opposite to the asRNAs. Sense sRNAs are within an ORF that is transcribed on the same strand as the sRNA. Intergenic sRNAs are found in intergenic regions (IGRs) between ORFs. Partial overlapping sRNAs occur when the 5' or 3' end of the sRNA overlaps with the 5' or 3' end of an ORF. Partial overlapping on both ends sRNAs occur when the 5' or 3' end of an ORF and the 3' of the sRNA with the 5' or 3' end of another ORF.

indicates that many of the putative sRNAs have proximal promoter sites and supports the notion that they are independently transcribed.

Next, we used TransTermHP,²⁴ a computational method to detect Rho-independent transcription terminators, to predict the locations of terminators in the *R. capsulatus* genome. We associated a terminator to a putative sRNA if the terminator was within 500 nts downstream from the predicted 3' end of the sRNA as described by Kingsford *et al.*²⁴ Of the 422 putative sRNAs, 130 (31%) had an associated predicted Rho-independent transcription terminator, whereas only 8.15% of the random genomic sequences did. Moreover, as depicted in Fig. 2C, there was a distinct peak in the probability that the 3' ends of the sRNAs were located 7 nts from the closest downstream terminator, whereas the random sequences' density function had a uniform distribution.

Based on the putative sRNAs' genomic contexts, we classified the sRNAs as either "intergenic" if located in intergenic regions (IGRs), "antisense" if located within an annotated gene and transcribed on the strand opposite to this gene, "partially overlapping" if the 5' or 3' end of the sRNA overlaps the 5' or 3' end of an annotated gene, "partially overlapping on both ends" if the 5' end of the sRNA overlaps an annotated gene and the 3' end of the sRNA overlaps another annotated gene, or "sense" if located within an annotated gene and transcribed on the same strand as this gene (Fig. 3). 150 sRNAs were intergenic, 186 were partially overlapping and 46 were partially overlapping on both ends. These amounts were 6.6, 5.2 and 2.6 times more than expected, respectively, if the locations were randomly distributed over the genome (Fig. 2D). In contrast, 28 antisense sRNAs (asRNAs) and 12 sense sRNAs were detected, which is 6.3 and 14.1 times less than expected, respectively (Fig. 2D).

As putative sRNAs had clearly distinct characteristics from random sequences, we decided to apply machine learning approaches (classifiers) to obtain a model to quantify the probability of a sequence being a bona fide sRNA. To derive the model, we selected as predictors (attributes) the free energy of the predicted secondary structure of the sRNA, the distance to a predicted promoter site, the distance to a Rho-independent terminator, and the sRNA genomic context. The genomic context included distance to the closest "left" neighboring ORF, distance to the closest "right" neighboring ORF, and whether the sRNA was on the same strand as the closest neighboring annotated ORFs. We refer to an annotated ORF located at the 5' end of a sRNA on the forward strand or an annotated ORF located at the 3' end of a sRNA on the reverse strand as "left," and an annotated ORF located at the 3' end of a sRNA on the forward strand or an annotated ORF located at the 5' end of a sRNA on the reverse strand as "right" (illustrated in Fig. S1). To create the model, we considered those sRNAs with intertaxa homologs in the sRNA collection or conserved in the genome of at least two other bacterial species, and sRNAs with hypothetical equivalogs (Fig. 1) as "bona fide sRNAs." We randomly chose 33 of these 41 bona fide sRNAs as positive instances and 98 random sequences as negative instances to train the classifiers. We then evaluated the classifiers' performances on the remaining 8 bona fide sRNAs and 4322 random sequences. We applied three machine learning approaches, namely, logistic regression, linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA).²⁵ Among these three methods,

logistic regression had the highest recall rates at the lowest false positive rate (Fig. S2A-C). Details about the logistic regression model obtained are given in the Materials and Methods section. At a probability cut-off of 0.6, the logistic regression model retrieved 66.25% of the positive test instances and only 4.7% of the random sequences. We then calculated the probability of being a bona fide sRNA using the logistic regression model for all 422 putative sRNAs. Of the 422 putative sRNAs, 109 (26%) scored a probability > 0.6 (Fig. S2D). At the estimated false positive rate, only five of these 109 sRNAs would be expected to be false positives. We expect that assigning a confidence estimate for being a bona fide sRNA to a given putative sRNA will help prioritize sRNAs for experimental validation. A limitation of this analysis is that, as the majority of positive instances used to learn the logistic regression model were intergenic or partially overlapping sRNAs, the logistic regression model underestimates the probability of asRNAs being bona fide sRNAs. These analyses need to be replicated in other bacterial species with a larger number of confirmed sRNAs to corroborate these findings and obtain better performance estimates. Table S1 contains the full description of all putative sRNAs, including their estimated probabilities of being bona fide sRNAs.

Identification of a putative tRNA-derived sRNA locus

We observed a putative intergenic sRNA (sRNA00295) found to be conserved in the genomes of 16 other bacterial species without a homologous sRNA in the sRNA collection or the RNA databases. This sRNA lacked a homologous sRNA of known function and we decided to inspect it further. The sequence of sRNA00295 was identical to the 3' region of the four tRNA-Met genes found in the *R. capsulatus* chromosome. The homology with the tRNAs makes interpreting the RNAseq read data somewhat challenging, as reads originating from



Figure 4. Genomic context and predicted secondary structure of a putative tRNA-derived sRNA locus (sRNA00295). The top panel shows sRNA00295's genomic context indicating distance to the closest protein-coding genes. The middle panel illustrates read depth coverage, location of predicted promoter site, and location of Rho-independent terminator (panel generated using Integrative Genomics Viewer version 2.3.72). The numbers of reads mapped for the SB1003 and the *ctrA* mutant strain were 472 and 462, respectively, as calculated by htseq-count. The bottom panel shows a multiple sequence alignment and predicted consensus secondary structure obtained using LocARNA. Colored nucleotides indicate correspondence between positions in the alignment and the RNA structure.

the tRNAs could be mapping onto this putative sRNA locus, and *vice versa*. However, a promoter site and Rho-independent terminator were predicted to flank this putative sRNA. We also checked this region in an additional unpublished data set based on differential RNA-seq (dRNA-seq), which identifies 5' ends of RNAs that originate from transcription initiation as opposed to RNA processing,²⁶ and a 5' end was identified at this location (Grüll *et al.*, unpublished). There have been recent discoveries of tRNA-derived sRNAs, which have been implicated in different regulatory processes.^{27,28} If genuine, this sRNA would instead represent an independent tRNA-derived fragment locus, and this warrants future investigation. Fig. 4 depicts sRNA00295's genomic context and predicted secondary structure.

To gain insight into the likely functional role of this putative sRNA, we used the CopraRNA web server²⁹ to predict sRNA00295's targets. Despite recent advances, most sRNA target prediction programs have a high false positive rate; CopraRNA, which requires at least three homologous sequences to predict targets, has twice the prediction accuracy of other sRNA target prediction programs.³⁰ Table 3 shows the top 10 sRNA00295 targets predicted by CopraRNA (the complete CopraRNA results, which includes all 76 predicted targets are listed in Table S2). To quantify protein interactions among sRNA00295's 76 predicted targets, we used the Search Tool for the Retrieval of Interacting Genes/Proteins (STRING, version 10.0) database of physical and functional interactions.³¹ Compared with similarly sized randomly selected protein sets, sRNA00295's 76 predicted targets have significantly more interactions among themselves (PPI enrichment p =1.13E-08), with 28 interactions as compared with eight for random protein sets. We also tested for functional enrichment among sRNA00295's 76 predicted targets using STRING, but no functional enrichment was found.

Functional and protein-interaction enrichment of potential cis-targets of putative antisense and partially overlapping sRNAs

To obtain insight into the biological processes potentially regulated by the antisense and partially overlapping putative sRNAs, we assumed that they were *cis*-acting and examined the 265 overlapping protein-coding mRNAs for functional and protein interaction enrichment using STRING. As antisense and partially overlapping sRNAs have been shown to also

Table 3. Top 10 targets predicted by CopraRNA for sRNA00295 a putative tRNAderived sRNA locus.

Gene ID	Description	
RCAP_rcc01474	amino acid permease	
RCAP_rcp00009	Lacl family transcriptional regulator	
RCAP_rcc00101	ABC transporter permease	
RCAP_rcc02606	mammalian cell entry domain-containing protein	
RCAP_rcc00024	glutaryl-CoA dehydrogenase	
RCAP_rcc01400	signal transduction histidine kinase	
RCAP_rcc00616	acriflavine resistance protein B	
RCAP_rcc00505	type II secretion system protein E	
RCAP_rcc01291	kinetochore Spc7 domain-containing protein	
RCAP_rcc01291	TetR family transcriptional regulator	

Table 4. Biotin-labeled probes for detection of selected sRNAs on Northern blots.

sRNA	Oligo sequence (5' to 3')	
sRNA00385	BIO-GCGCAGTTGACGCGCCGTCT	
sRNA01029	BIO-GGAAACCGGGCGCGGGAACC	
sRNA00848	BIO-TCAAGCCTCTGAGGAAGGTC	
sRNA01129	BIO-GGGGCTGTTGACCGCCCGCC	

regulate gene expression in trans,³² this approach likely missed additional regulatory targets of these putative sRNAs. Nevertheless, the set of *cis*-targets showed a significant enrichment of genes involved in primary metabolic process (28 genes, FDRcorrected p = 1.97E-5), photosynthesis (16 genes, FDR-corrected p = 3.98E-5), compound binding (24 genes, FDR-corrected p = 0.004), and of genes encoding parts of macromolecular complexes (17 genes, FDR-corrected p = 3.2E-7). The complete functional enrichment results are provided in Table S3. We also investigated whether putative cistargets were co-expressed based on previously determined *R. capsulatus* gene co-expression modules,¹⁶ and found that *cis*targets showed a significant accumulation in two gene coexpression modules (13 genes in the midnightblue module, FDR-corrected p = 0.002; and 7 genes in the salmon4 module, FDR-corrected p = 0.003). Additionally, there were significantly higher interactions among the network of *cis*-targets (PPI enrichment p = 0), with 528 interactions as compared to 204 for random protein sets. This indicates that several of the likely cis-targets interact and are co-expressed, and supports the notion that sRNAs play a regulatory role in these processes.

Effects of loss of ctrA on sRNA expression

We investigated whether putative sRNAs were differentially expressed between two R. capsulatus strains: the genomesequenced strain, SB1003, and its ctrA null mutant derivative, SBRM1. CtrA is a two-component/histidyl-aspartyl phosphorelay response regulator that affects many processes in R. capsulatus such as motility and gene transfer agent production.³³ In Caulobacter crescentus, where it is an essential protein and controls many cell cycle-related process, CtrA was shown to regulate expression of sRNAs as part of its regulon.³⁴ Fig. S3 illustrates the distribution of the normalized log2 fold change of the sRNAs' read counts between the two strains. Although more samples are required to have enough statistical power to identify statistically differentially expressed sRNAs, the vast majority of sRNAs do not appear to be differentially expressed. However, 18 sRNAs had an absolute log2 fold change >3, suggesting possible differential expression between the strains. Among these 18 sRNAs, there are 2 asRNAs, 7 intergenic, 8 partially overlapping, and 2 partially overlapping on both ends sRNAs. Nine of the 14 ORFs overlapped by the antisense and partially overlapping sRNAs were previously identified as affected by the loss of $CtrA^{15}$ (p = 4.14E-10, Hypergeometric test), including genes encoding the flagellar protein MotB (rcc00006), the flagellar hook-associated protein FlgK (rcc00008), an Hpt domain-containing protein (rcc00180), and the DNA-protecting protein DprA (rcc03098). We also investigated whether these 14 ORFs overlapped by potential differentially expressed sRNAs were co-expressed based on previously

determined *R. capsulatus* gene co-expression modules and, indeed, they were significantly over-represented in two modules: pink (6 genes, FDR-corrected p = 1.05E-5) and orange (3 genes, FDR-corrected p = 2.9E-4). The orange module was identified as associated with the production of RcGTA¹⁶ and the DprA protein is required for uptake of DNA from RcGTA particles by recipient cells,³⁵ thereby adding sRNAs as another regulatory mechanism involved in controlling RcGTA-mediated gene exchange in *R. capsulatus*.¹¹ As all of the potentially differentially expressed sRNAs are *R. capsulatus*-specific, we were unable to use CopraRNA to predict potential targets of the intergenic sRNAs.

Experimental validation of putative sRNAs using Northern blot analysis

We chose four putative sRNAs to evaluate by Northern blotting. These were sRNA00385, sRNA01029, sRNA00848, and sRNA01129, representing four R. capsulatus-specific intergenic sRNAs, three of which showed differential expression between the wild type and ctrA mutant strains, as evaluated by read counts in the RNA-seq data. We purposefully chose three of the targets due to their predicted differential expression to help with interpretation of the Northern blots as previous studies have detected multiple bands on Northern blots probed for sRNA detection.³⁶ These differentially expressed sRNAs are also candidates for future investigation for potential roles in the regulation of CtrA-affected processes, such as the production of RcGTA. As expected due to the program's limitation with respect to correctly identifying the 5' and 3' boundaries of sRNAs,⁹ the bands detected for each of the sRNAs were larger than predicted by sRNA-Detect. Manual inspection of the sequence read data allowed us to estimate the boundaries and sizes of these sRNAs more accurately (Fig. 5) to match the sizes estimated on the Northern blots, and we identified putative promoter sequences for these sRNAs (Fig. 6) that agree with a previously identified R. capsulatus consensus promoter sequence.³⁷



Figure 6. Identification of putative promoter -10 and -35 sequences for four experimentally confirmed sRNAs. (A) Predicted promoter sites upstream of each of the sRNAs. The nucleotide spacing between the motifs is indicated. (B) The frequency of bases found at each position is indicated by the size of the colored letters, created with Weblogo 3.0.⁵¹ (C) Consensus promoter sequence based on promoters identified in a previous study.³⁷

sRNA00385 was predicted to have a size of 189 nts based on sRNA-Detect. Examination of the sequence reads for this region suggested an actual size of 249 nts (Fig. 5). A putative promoter site was found upstream of the predicted 5' end (Figs. 5 and 6) although in this case the -10 site was centered 18 nts upstream of the predicted 5' end, possibly indicating either poor read coverage at the 5' end as frequently found in RNA-seq,³⁸ or variable length spacing in the promoter elements.^{39,40} This putative sRNA showed similar, high levels of expression in the RNA-seq data from both strains. The Northern blot showed a major band at approximately 230 nts (Fig. 7). There were several additional bands detected on this blot, most of which were present in both strains. These presumably result from non-specific hybridization of the probe to additional RNAs, as has been observed in previous studies detecting sRNAs by this method.³⁶

sRNA01029 was predicted to have a size of 52 nts by sRNA-Detect. Inspection of the sequencing data for this sRNA suggested a size of 68 nts and a -10 element was identified centered 12 nts upstream of the predicted sRNA's



Figure 5. Read depth coverage plots and genomic locations for the experimentally confirmed sRNAs. Parts of the neighboring genes are shown with green arrows indicating their direction in the genome. Their relative distance to the coverage plots is not to scale. Predicted promoter -10 and -35 elements are depicted as black boxes with white arrows inside, and the sequences are given in Fig. 6 and below. The distance of the promoter relative to the 5' end of the corresponding sRNA is also not to scale. The sRNA sequencing reads are presented as purple plots with an indication of the sRNA's predicted size on top. Blue bars mark the predicted 5' ends and orange bars the predicted 3' ends of the sRNAs. The sRNAs' 5' and 3' end sequences and the -10/-35 elements are shown underneath the plots in their respective 5'-3' orientations.



Figure 7. Northern blot images of the experimentally confirmed sRNAs. RNA from the genome-sequenced strain, SB1003, and the *ctrA* mutant strain were run in the left and right lane, respectively, of each gel. The sequences of the biotin-labeled probes are given in Table 4. The sizes for the corresponding ladder bands are indicated on the left of each blot image, and the number on top of each image identifies the corresponding sRNA probe.

5' end (Figs. 5 and 6). The sRNA was predicted to be more highly expressed in the wild type strain based on read count data (approximately 3:1, Table S1). The Northern blot showed several bands in both strains, with one band at approximately 65 nts that was present at higher levels in the wild type strain in comparison to the *ctrA* mutant (Fig. 7).

sRNA00848 was predicted to have a size of 71 nts by sRNA-Detect, with inspection of the sequencing data suggesting a size of 91 nts. A putative promoter sequence was identified upstream of the predicted 5' end (Figs. 5 and 6) but, as with sRNA00385, the -10 sequence was centered more than 10 nts upstream (25 nts). This sRNA was only detected in the RNAseq data from the wild type strain and the Northern blot showed a band at approximately 78 nts only in RNA from the wild type strain (Fig. 7).

sRNA01129 was predicted to have a size of 69 nts based on sRNA-Detect, and this matched the predicted size from manual inspection of the sequencing data. We found a putative promoter with a -10 element centered 7 nts upstream of the predicted 5' end (Figs. 5 and 6). This sRNA was detected at a much higher level in the wild type strain RNA-seq data compared to the *ctrA* mutant (28:1, Table S1). The Northern blot showed a band at approximately 60 nts that was present in the wild type strain but not detected in the *ctrA* mutant (Fig. 7).

Conclusions

Using RNA-seq data we have identified 422 putative sRNAs in *R. capsulatus*: 24 sRNAs with hypothetical equivalogs, 40 sRNAs with putative inter-taxa homologs, 60 sRNAs with putative intra-genus homologs and 298 potential *R. capsulatus*-specific sRNAs. To help prioritize further investigations into these sRNAs, we have bioinformatically characterized these sRNAs and used logistic regression to quantify the probability of a putative sRNA being a bona fide sRNA. Using the logistic regression model, 109 (or 26%) of the 422 putative sRNAs were assigned a probability greater than 0.6 of being a bona fide sRNA; at the estimated false positive rate of 4.8%, only five out

of these 109 sRNAs are expected to be false positives. Analysis of a strain lacking the important response regulator CtrA identified 18 putative sRNAs that were differentially expressed relative to the wild type strain. This indicates that effects on the levels of sRNAs is another means by which the CtrA phosphorelay regulates processes in *R. capsulatus*. We experimentally confirmed the existence of four of the putative sRNAs by Northern blot analysis, and validated the differential expression that was predicted from the RNA-seq data analysis for three of these. The abundance of sRNAs detected in *R. capsulatus* indicates that a potential extra layer of regulatory complexity exists in this species. Revealing the functional roles of these sRNAs will improve our understanding of the mechanisms *R. capsulatus* employs to regulate its physiology.

Materials and methods

R. capsulatus growth and RNA isolation

R. capsulatus cultures were grown under anaerobic phototrophic conditions at 35°C in complex YPS medium⁴¹ until four hours after reaching stationary phase. The culture was mixed 5:1 with 95% ethanol and 5% saturated phenol,⁴² the cells were pelleted by centrifugation, the supernatant was removed, and the cell pellets were frozen in dry ice/ethanol and stored at -80°C until RNA isolations were performed. sRNA purification was performed with the NucleoSpin[®] miRNA kit (MACHEREY-NAGEL) following the manufacturer's protocol for purification of the small RNA fraction (<200 nts).

Library preparation and sequencing

The isolated small RNA fraction was used for RNA library preparation for sequencing using an Ion Torrent Personal Genome Machine (PGM; Thermo-Fisher). The RNA quality was checked prior to library preparation using an Agilent Bioanalyzer (Agilent Technologies). Library preparation followed the manufacturer's recommendations for small RNA libraries with the RNA-seq Kit v2 (Thermo-Fisher). The library was amplified using an Ion Torrent One Touch 2 system. The samples were loaded individually on 316 v2 chips and sequenced with the number of flows set to 550.

Processing of RNA-seq data

The RNA-seq data quality was verified using the FastQC tool (version 0.10.0) and reads were filtered and trimmed using the fastq_quality_trimmer available in the FASTX Toolkit (version 0.0.13.2) with a quality threshold of 22 and minimum read length of 28 nucleotides. Filtered and trimmed reads were mapped to the *R. capsulatus* genome using the Torrent mapper tmap (version 3.0.1), executed with the parameters: -B 18 -a 2 -v stage1 map1 map2 map3. Mapping statistics were obtained using samtools.⁴³

Detection of sRNAs from RNA-seq data

sRNAs were predicted from mapped RNA-seq data using sRNA-Detect.⁹ sRNA-Detect constructs a coverage vector using

the function GenomicArray available in HTSeq⁴⁴ (version 0.5.4p5) and then goes through the genomic intervals in the coverage vector and finds continuous segments between 20 and 250 nucleotides long with similar numbers of reads, with a maximum percentage change of 3% allowed in the average number of reads. A minimum of 10 reads across all samples was required to consider a transcript as expressed. sRNA-Detect is available at www.cs.mun.ca/~lourdes. Predicted transcripts overlapping to tRNAs and rRNAs were removed from the putative sRNA set using the tool intersectBed available in BEDtools⁴⁵ (version 2.25).

Collection and analysis of sRNAs from other bacterial species

Published studies performing genome-wide identification of sRNAs using RNA-seq data were identified (Table 1), genomic coordinates of the putative sRNAs were collected, and the corresponding sRNA sequences were obtained using the tool fasta-FromBed available in BEDtools.

Bioinformatic analysis of sRNAs

Sequence conservation of putative sRNAs was determined by identifying reciprocal best BLAST matches between pairs of species (Table S4). The program blastn (version 2.2.30+) was executed with an E-value cut-off of 1E-4, a best_hit_overhang of 0.1 and task mode of "blastn." Rfam matches were obtained using the batch search functionality in the Rfam database (version 12.1). If an sRNA had multiple Rfam matches only the most significant match was considered. All 30581 sRNA sequences in BSRD were downloaded (May 2015) and a BLAST database was created with these sequences. BSRD matches per sRNA were obtained using blastn with the same settings as for the homology search. If an sRNA had multiple BSRD matches only the match with the lowest E-value was considered. The RNAcentral database (release 5) was downloaded (May 2016) and nhmmer⁴⁶ (version 3.1b2) with an E-value cutoff of 1E-3 was used to identify RNAcentral matches for each putative sRNA. If an sRNA had multiple RNAcentral matches only the most significant match was considered. CentroidFold with parameters -e "CONTRAfold" and -g 4 was used to predict the secondary structure of putative sRNAs and random genomic sequences. Sequences of the sRNAs including 150 nts upstream of the predicted 5' end were obtained using slopBed and fasta-FromBed and promoter sites were predicted using BPROM with default values. Rho-independent terminators in R. capsu*latus* genome were predicted using TransTermHP with default values and providing an annotation file with the coordinates of the protein-coding genes. The numbers of reads mapped to the putative sRNAs per strain were calculated using htseq-count available in HTSEQ. Normalized log2 fold changes between the two R. capsulatus strains were obtained using edgeR⁴⁷ (version 3.12.1). All results were compiled, processed and visualized using R (version 3.2.4).

To apply machine learning approaches, we represented a putative sRNA or a random genomic sequence as a numerical vector *X* consisting of seven numerical predictors (input variables); namely, free energy of the secondary structure, distance

ranging from [-150, 20] nts to the -10 predicted promoter site (if no promoter site was predicted in that range a value of -1000 was used), distance to terminator ranging from [0, 500] nts (if no terminator was predicted within this distance range a value of 1000 was used), distance $(-\infty, 0]$ nts to closest left ORF, a binary number indicating whether the RNA is transcribed on the same strand as its left ORF (1 if transcribed on same strand), distance $[0, +\infty)$ to closest right ORF, and a binary number indicating whether the RNA is transcribed on the same strand as its right ORF. For training the classifiers, 33 of the 41 putative sRNAs deemed as bona fide sRNAs were randomly selected as positive instances, and 98 of the 4420 random genomic sequences were randomly selected as negative instances. The remaining sequences were used for testing. Logistic regression was applied using the R function glm (with family = binomial), and cross-validation was performed using the function cv.glm from the R package boot (version 1.3-18). LDA and QDA were applied using the lda and qda functions from the R package MASS (version 7.3-45). Performance measurements were calculated using the R package ROCR⁴⁸ (version 1.0-7). For the classifiers' performance comparison, we used recall and false positive rates. Recall indicates the proportion of testing positive instances that are predicted to be bona fide sRNAs by a given approach at a certain probability threshold (i.e., true positives (TP) divided by the total number of positive instances (P)). The false positive rate is the proportion of negative instances that are predicted to be bona fide sRNAs by a given approach at a certain probability threshold (i.e., false positives (FP) divided by the total number of negative instances (N)). The logistic regression estimates the parameter θ to model $p(X) = e(\theta_0 + \theta_1 X_1 + \dots + \theta_p X_p) / (1 + e(\theta_0 + \theta_1 X_1 + \dots + \theta_p X_p))$ $(\theta p X p)$) where X is the vector of attributes representing an instance, e is the base of the natural logarithm, p is the number of attributes in X, and Xi is the value of attribute i. The parameter θ was chosen to maximize the likelihood function. The value of the estimated parameters was $\theta = [-2.02, -0.037, -5.8e-4]$ -2.1e-3, -0.011, 0.25, 5e-3, 0.38]. Intuitively, the model learnt makes sense; for instance, decreasing the free energy increases the probability of being a bona fide sRNA, and decreasing the distance to a terminator increases the probability of being a bona fide sRNA. We used these parameters' values to calculate the probability of being a bona fide sRNA for all putative sRNAs. A probability cut-off of 0.6 was chosen as the optimal cut-off to have high recall while maintaining a low false positive rate.

Detection of sRNAs by Northern blotting

Purified sRNA was eluted in 30 μ l of nuclease-free water. The water was subsequently evaporated using a vacuum centrifuge (Thermo Scientific, Savant DNA120 SpeedVac Concentrator) for 30 minutes at high vacuum setting. The RNA was then dissolved in 20 μ l of nuclease-free water to increase the initial concentration.

A denaturing 15% polyacrylamide gel containing 7 M urea was used to separate the sRNAs. The gel was pre-run for 30 minutes at 18 mA (100 V) in 1X TBE buffer (89 mM Tris, 89 mM boric acid, 20 mM EDTA; pH 8.0). A total of 10 μ g of RNA was prepared in a 10 μ l sample for electrophoresis and mixed with 5 μ l of 3X loading buffer (95% (v/v) formamide, 20 mM EDTA, Bromphenol blue and Cyanol xylene) such that paired wild type and mutant samples contained the same amount of RNA. The low-range single stranded RNA ladder (NEB; N0364S) was included for size reference. The gels were run for 80 minutes at 18 mA (100 V) in 1X TBE buffer. After electrophoresis, the lanes containing one set of samples with a corresponding ladder were cut from the gel and stained in ethidium bromide for 15 minutes before taking an image. The remaining gel was cut into pieces containing paired wild type and mutant sRNA samples and each pair transferred to a Hybond-N⁺ nylon membrane (Amersham) by electro-blotting in 1X SSC buffer (3 M NaCl, 30 mM Sodium Citrate) for 2 hours at 250 mA (4 V). The RNA was cross-linked to the membranes by exposing them to 120000 μ J cm⁻² (UVC500 UV Crosslinker; Hoefer) and the membranes were then dried at 50 °C for 30 minutes.

The membranes were rolled with hybridization mesh and pre-hybridized for 3 hours in 10 ml pre-hybridization solution containing 10 μ g ml⁻¹ of salmon sperm DNA at 40 °C in a hybridization oven (Model 5420; VWR). After the pre-hybridization step, 50 μ g ml⁻¹ of biotin-labeled probe⁴⁹ was added directly to the pre-hybridization solution and the membranes were hybridized with the probe for 16 hours at 40 °C. Probe sequences are given in Table 4. After hybridization, the membranes were washed twice in 2X SSC/0.1% SDS for 15 minutes at 40 °C, with a final wash in 0.1X SSC for 15 minutes at room temperature.⁵⁰ The Chemiluminescent Nucleic Acid Detection Module (catalog # 89880; Thermo-Fisher) was used for probe detection following the manufacturer's recommendations. Images were captured using an ImageQuant LAS4000 (General Electric Canada). The resulting images were adjusted for brightness and contrast using Adobe Photoshop CC 2017. The images of the ethidium bromide-stained portions of the corresponding gels were used to construct standard curves to allow estimation of the sizes of bands detected on the blots.

Disclosure of potential conflicts of interest

No potential conflicts of interest were disclosed.

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