

β-strand segments prediction based on protein sequence and predicted neighboring structural information

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Introduction Introduction

Existing secondary structure predictors perform relatively poorly on β-strands when compared with the prediction of helices/coils [1]. Our analysis of 6 recently published/popular predictors (PROTEUS [2], PSI-PRED [3], SABLE [4], SPINE [5], SSpro [6] and YASPIN [1]) reveals that their SOVe ranges between 61 and 73% and that up to 18% of strand segments are never predicted. Recent works suggest that ensemble-based approaches may provide improvements [7] and show that correlations between neighboring secondary structures are stronger than between neighboring residues [8]. Existing secondary structure predictors perform relatively poorly on β-strands when compared with the prediction of helices/coils [1]. Our analysis of 6
recently published/popular predictors (PROTEUS [2], PSI-PRED [3], SA

Materials & Methods Materials & Methods

We propose a novel ensemble-based approach that exploits predicted local and global structural information to predict β-strand residues. Our method is intended to improve the coverage (by method is intended to improve the coverage (by finding strands omitted by other methods) and quality (by improving SOVe) of strand predictions when compared with the current secondary structure predictors. We use the primary sequence, secondary structure predicted by SSpro, SPINE and PSI-PRED (three best-performing template-free PSI-PRED (three best-performing template-free predictors), and residue depth predicted with RDpred [9] to compute novel features that reveal local structures in the neighborhood of the predicted residue, and global information from the entire sequence. The method generates predictions by feeding a small set of 11 features, which were found by feature selection on a training dataset, as by feeding a small set of 11 features, which were
found by feature selection on a training dataset, as
an input to a logistic regression classifier and the predictions are merged with the strand residues predicted by the best performing (on the training set) SSpro. set) SSpro. finding strands omitted by other methods) and quality (by improving SOVe) of strand predictions when compared with the current secondary predictors), and residue depth predicted with RDpred [9] to compute novel features that reveal local structures in the neighborhood of the predicted residue, and global information from the entire sequence. The method gene

Experimental comparison between the proposed and competing predictors on the three independent test datasets, Test (432 proteins), CASP8 (118), and CASP8 (8 template free proteins). The strands were considered as found when at least 60 % of residues or one residue were correctly predicted, see columns 3 and 4, respectively.

Results Results

Tests show that the proposed method achieves SOVe of 74.6% and 72.2%, on 432 low-identity chains from the test dataset (at max pairwise identity of 40% within the test set and between test and training sets) and a set of 118 CASP8 targets, respectively. To compare, best performing secondary structure predictors based on 3-state accuracy, SSpro and SPINE, obtain SOVe of 73.1/71% and 67.5/68.5% on these two datasets, respectively. In addition, our approach misses only 12% and 11.7% of strand segments, while SSpro misses 16.3/16.8% and SPINE misses 15/15.2% of strand addition, our approach misses only 12% and 11.7% of strand segments, while SSpro misses 16.3/16.8% and SPINE misses 15/15.2% of strand
segments on the two datasets, respectively. Results for 8 template-free CASP8 proteins model outperforms other considered methods. PROTEUS and YASPIN over-predict strand residues on the test and template-free sets, respectively, see Qe values. When compared with SSpro (our base predictor) the proposed method improves SOVe between 1.5 and 4.7. Our study constitutes a step towards designing an accurate β -strand predictor that would, in the future, facilitate prediction of β -strand residue pairs and β -sheets.

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