POLSAR DATA ONLINE CLASSIFICATION BASED ON MULTI-VIEW LEARNING

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Abstract

Polarimetric synthetic aperture radar (PolSAR) plays an indispensable part in remote sensing. With its development and application, rapid and accurate online classification for PolSAR data becomes more and more important. In this paper, we propose an online multiview learning method based on the passive aggressive algorithm, named OMVPA, for PolSAR data real-time classification. The OMVPA method makes full use of the consistency and complementary properties of different types of features. Experimental results on real PolSAR data demonstrate that the proposed method maintain a smaller mistake rate compared with other methods.

Motivation

- PolSAR data are acquired in a consecutive sequence and usually large-scale, and can be depicted by polarimetric, texture and color features regarded as multiple views.
- The existing PolSAR classification algorithms:
  - use a single type of features or the concatenate features from different views
  - do not update the classifier when a newly arrived sample is misclassified
  - have to be retained on the whole new dataset
- To address the above issues, an online multi-view learning algorithm is proposed for PolSAR data real-time classification.

Proposed method

- Optimization problem

$$\{\boldsymbol{w}_{t+1}^{(1)},\boldsymbol{w}_{t+1}^{(2)}\}=\underset{\boldsymbol{w}^{(1)},\boldsymbol{w}^{(2)}}{\operatorname{argmin}}\frac{\lambda_1}{2}\|\boldsymbol{w}^{(1)}-\boldsymbol{w}_t^{(1)}\|^2+\frac{\lambda_2}{2}\|\boldsymbol{w}^{(2)}-\boldsymbol{w}_t^{(2)}\|^2+d|(\boldsymbol{w}^{(1)}\cdot\mathbf{x}_t^{(1)})-(\boldsymbol{w}^{(2)}\cdot\mathbf{x}_t^{(2)})|+c\xi^2$$

$$\text{s.t.}\quad l(\boldsymbol{w};(\mathbf{x}_t,y_t))\le\xi.$$

where $l(w;(\mathbf{x}_t,y_t))=\max\{0,1-y_t(r(\boldsymbol{w}^{(1)}\cdot\mathbf{x}_t^{(1)})+(1-r)(\boldsymbol{w}^{(2)}\cdot\mathbf{x}_t^{(2)}))\}.$

- Update steps

Lagrangian multiplier method

$$\boldsymbol{w}_{t+1}^{(1)}=\boldsymbol{w}_t^{(1)}+\frac{1}{\lambda_1}(\tau r y_t-ds)\mathbf{x}_t^{(1)}\qquad(3)$$

$$\boldsymbol{w}_{t+1}^{(2)}=\boldsymbol{w}_t^{(2)}+\frac{1}{\lambda_2}(\tau(1-r)y_t+ds)\mathbf{x}_t^{(2)}\qquad(4)$$

$$\tau=\frac{l(\boldsymbol{w}_t;(\mathbf{x}_t,y_t))+dsy_t\left[\frac{r}{\lambda_1}\|\mathbf{x}_t^{(1)}\|^2-\frac{1-r}{\lambda_2}\|\mathbf{x}_t^{(2)}\|^2\right]}{\frac{r^2}{\lambda_1}\|\mathbf{x}_t^{(1)}\|^2+\frac{(1-r)^2}{\lambda_2}\|\mathbf{x}_t^{(2)}\|^2+\frac{1}{2c}}.\qquad(6)$$

Algorithm 1: Online Multi-view Learning Algorithm for Binary Classification

Input: Four positive scalars λ_1, d, r and c.
Initialization: $\boldsymbol{w}^{(1)}=\mathrm{rand}(1,\mathrm{length}(\mathbf{x}_1^{(1)}))$, $\boldsymbol{w}^{(2)}=\mathrm{rand}(1,\mathrm{length}(\mathbf{x}_1^{(2)}))$.
for $t=1,2,\ldots$ **do**
  Receive instances: $\mathbf{x}_t^{(1)}\in\mathbb{R}^m$ and $\mathbf{x}_t^{(2)}\in\mathbb{R}^n$.
  Compute the sign: $s=\mathrm{sign}((\boldsymbol{w}_t^{(1)}\cdot\mathbf{x}_t^{(1)})-(\boldsymbol{w}_t^{(2)}\cdot\mathbf{x}_t^{(2)}))$.
  Compute: $f_t=r(\boldsymbol{w}_t^{(1)}\cdot\mathbf{x}_t^{(1)})+(1-r)(\boldsymbol{w}_t^{(2)}\cdot\mathbf{x}_t^{(2)})$.
  Predict: $\hat{y}_t=\mathrm{sign}(f_t)$.
  Receive the correct label: $y_t\in\{-1,1\}$
  Compute the loss: $l_t=\max\{0,1-y_tf_t\}$.
  if $l_t>0$ **then**
    Compute the parameter τ according to (6).
    Update $\boldsymbol{w}_{t+1}^{(1)}$ and $\boldsymbol{w}_{t+1}^{(2)}$ according to (3) and (4).
  end if
end for

Experimental results

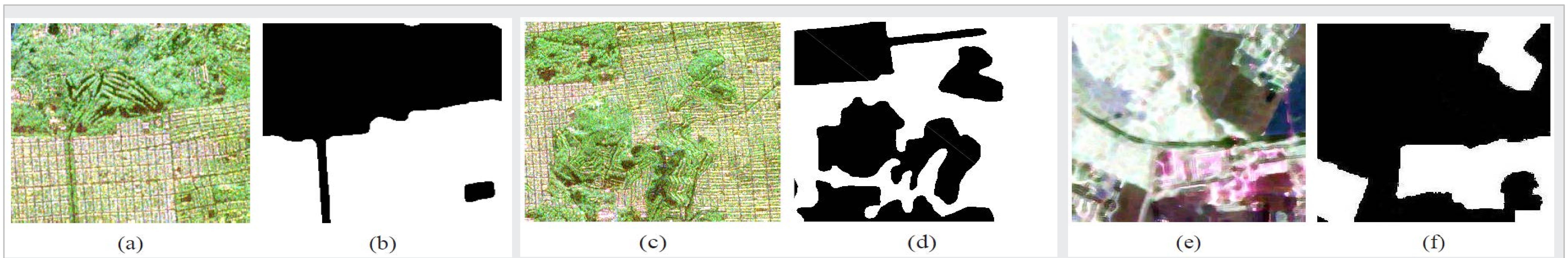
(a) (b) (c) (d) (e) (f)

Figure 1. Real PolSAR data. (a)(c)(e) The Pauli decomposition image of sanf1, sanf2 and oberp. (b)(d)(f) The ground truth map of sanf1, sanf2 and oberp.

Dataset/Methods	PA_Pol	PA_coltex	PA_Cat	AdaPA	OMVPA
sanf1	0.0782±0.0006	0.0875±0.0008	0.0551±0.0006	0.0617±0.0008	**0.0461±0.0005**
sanf2	0.2167±0.0010	0.2291±0.0013	0.2032±0.0011	0.1723±0.0004	**0.1536±0.0006**
oberp	0.2861±0.0007	0.2998±0.0014	0.2750±0.0007	0.2682±0.0009	**0.2163±0.0011**

Table 1. Average Online Mistake Rate on Real PolSAR Data

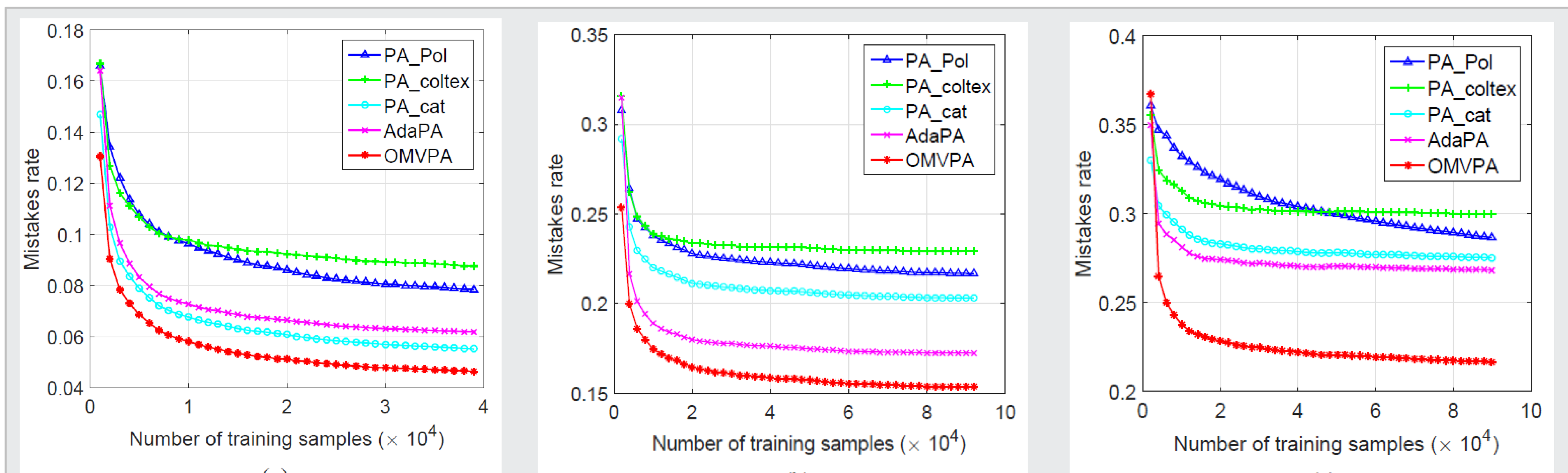

Figure 2. Comparison of error evolution curves. (a) Results on sanf1. (b) Results on sanf2. (c) Results on oberp.

Conclusions:

- For PA, the error on the concatenation features is lower than that on each view features.
- AdaPA algorithm has a higher error than PA_Cat on sanf1 due to the unreasonable disagreement constraint.
- OMVPA has the lowest average mistake rate and achieves about 1%, 2% and 5% improvements compared with the results of PA Cat and AdaPA, respectively..
- The online cumulative errors of all the algorithms consistently decrease when the number of online rounds increases.
- The comparison results of these methods in Fig. 2 are in accordance with the results in Table I.
- The proposed OMVPA algorithm almost consistently achieves the smallest mistake rate in the entire online classification process.