Dear reviewer RC4:

Thank you very much for the insightful comments. Thank you for giving us a choice to correct the shortcoming of our manuscript. We already carefully read your comments and revised the manuscript according to your suggestions. We hope that this revision will make our manuscript meet the publisher. The responses to the comments point by point are listed below. Please feel free to contact us with any questions. If the revised manuscript maybe exists the shortcomings, please tell us. We will try our best to continue to revise our manuscript in order to improve our manuscript. Really thank your insightful comments and help again!

Yours sincerely，

Regards,

Xiangbing Zhou

Reviewer #RC4:

The proposal is interesting, and the experiments conducted are good, however the manuscript presents many flaws in its present form.

1.In the abstract, it is better to improve some sentences and the innovation and achievement of the paper that comprise it from other similar work is ambiguous and is better to add to the abstract. The introduction is not organized well and the lack of consistency in the story's narration is apparent. Please improve it if possible. Some modifications in terms of eliminating such general and clear information are needed.

2. Literature review is a little bit insufficient, please add more recent good works by researchers..

3. The quality of the figure should be improved as much as possible. For instance, in Fig.1,...

4. What are the limitations behind this study? This topic should be highlighted in the Conclusion of manuscript.

5. The conclusions should be more concrete with data. Please improve them.

COMMENT 1: T In the abstract, it is better to improve some sentences and the innovation and achievement of the paper that comprise it from other similar work is ambiguous and is better to add to the abstract. The introduction is not organized well and the lack of consistency in the story's narration is apparent. Please improve it if possible. Some modifications in terms of eliminating such general and clear information are needed.

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to improve some sentences and the innovation and achievement of the paper that comprise it from other similar work is ambiguous and is better to add to the abstract. In addition, The introduction is reorganized and the consistency in the story's narration is improved. Some modifications in terms of eliminating such general and clear information are added in our revised paper. Please read our revised manuscript, thanks!

Abstract:Hyperspectral images contain abundant spectral and spatial information of the surface of earth, which increase the difficulties of data processing and analysis, and sample labeling. In this paper, local binary pattern (LBP), *sparse representation and mixed logistic regression model are introduced to propose a sample labeling method based on neighborhood information and priority classifier discrimination. Then, a hyperspectral remote sensing image classification method based on texture features and semi-supervised learning is implemented. The LBP is employed to extract features of spatial texture information from remote sensing images and enrich the feature information of samples. The multivariate logistic regression model is used to select the unlabeled samples with the largest amount of information, and the unlabeled samples with neighborhood information and priority classifier tags are selected to obtain the pseudo-labeled samples after learning. By making full use of the advantages of sparse representation and mixed logistic regression model, a new classification model based on semi-supervised learning is constructed to effectively achieve accurate classification of hyperspectral images. The data of Indian Pines, Salinas scene and Pavia University are selected to verify the validity of the proposed method. The experiment results show that the proposed classification method obtains higher classification accuracy and shows stronger timeliness and generalization ability.*

COMMENT 2: Literature review is a little bit insufficient, please add more recent good works by researchers..

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to add more recent good works by researchers, which can improve the reviews the literatures. Please read our revised manuscript, thanks!

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COMMENT 3: The quality of the figure should be improved as much as possible. For instance, in Fig.1,..

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to improve the quality of the figures. Please read our revised manuscript, thanks!

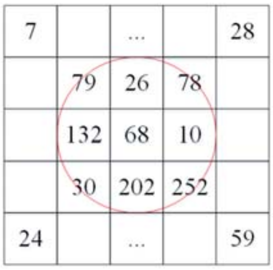

Figure1. The quantized texture feature form of one region

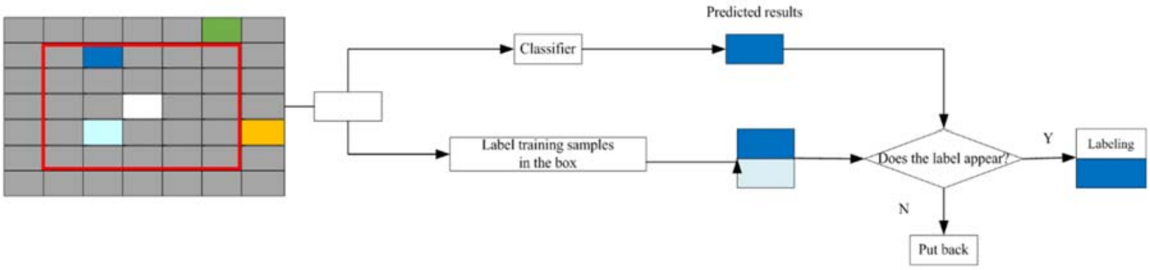

Figure 2. Sample labeling process based on neighborhood information and priority classifier discrimination

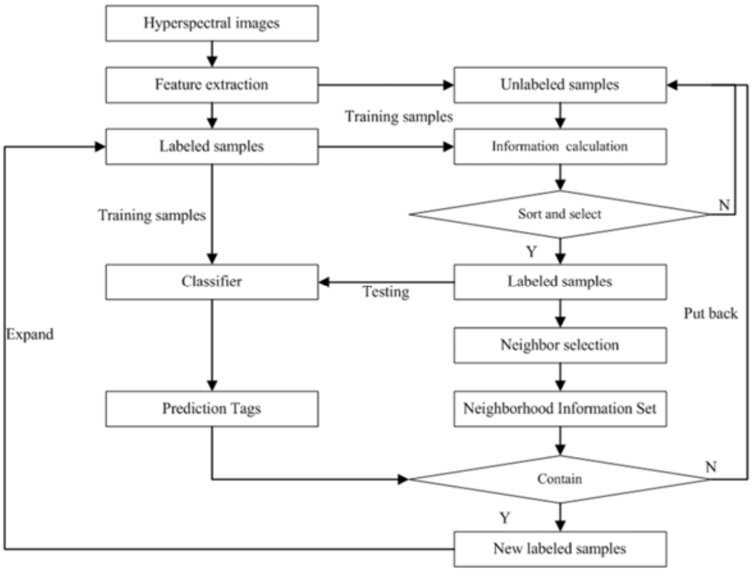

Figure 3. Hyperspectral image classification model based on texture features and semi-supervised learning

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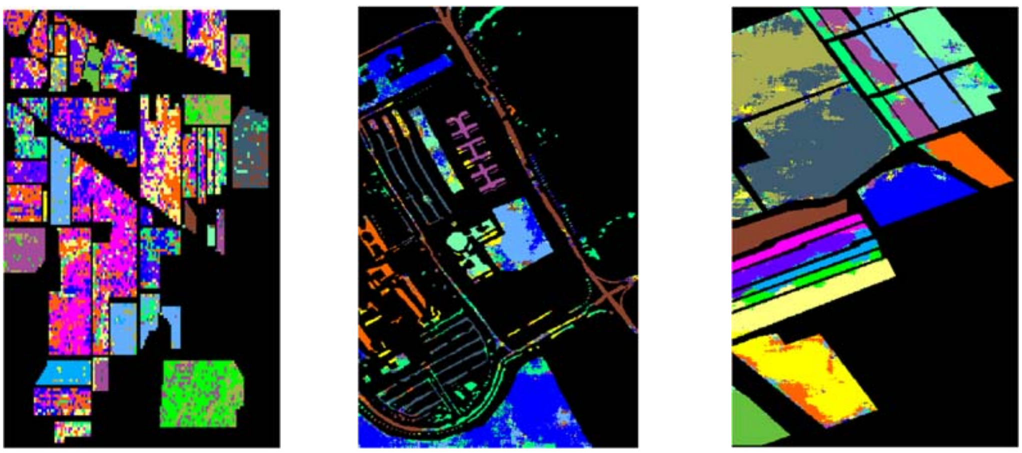
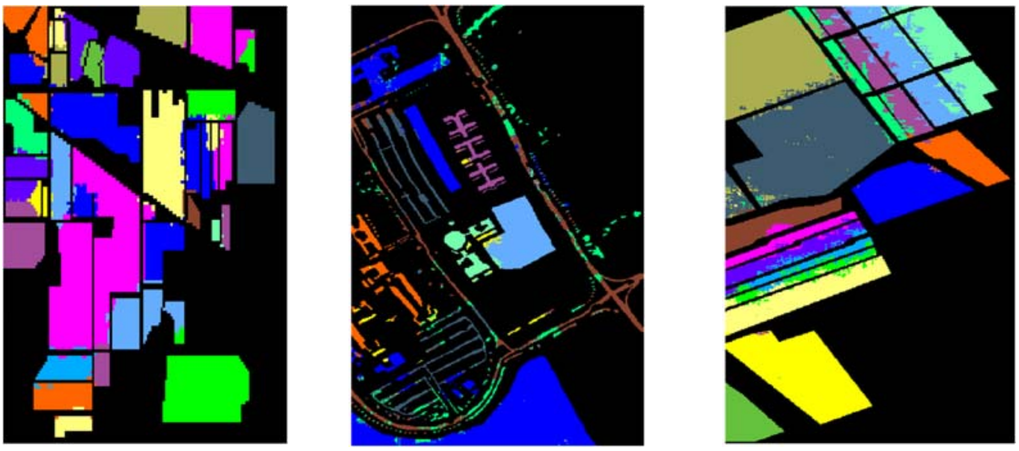


(a)Indian Pines (b)Pavia University (c)Salinas Scene

Figure 7 The classification results of the initial samples



(a)Indian Pines (b)Pavia University (c)Salinas Scene

Figure 8 The classification results of the labeling samples

COMMENT 4: What are the limitations behind this study? This topic should be highlighted in the Conclusion of manuscript.

RESPONSE: Thank you very much for the insightful comments. In this stud, the proposed classification method has the more computing time, so the next step should be more in-depth research to reduce the time complexity. Therefore, this topic has highlighted in the Conclusion of manuscript. Please read our revised manuscript, thanks!

5. Conclusion

However, the proposed classification method has the more computing time, so the next step should be more in-depth research to reduce the time complexity.

COMMENT 5: The conclusions should be more concrete with data. Please improve them.

RESPONSE: Thank you very much for the insightful comments. According to expert advice, we have substantially modified our manuscript in order to add more concrete with data in the conclusions. Please read our revised manuscript, thanks!

6. Conclusion

For the difficulties of hyperspectral image processing and analysis, a new sample labeling method based on neighborhood information and priority classifier discrimination is developed to implement a new hyperspectral remote sensing image classification method based on texture features and semi-supervised learning by introducing local binary model, sparse representation and mixed logistic regression model. The local binary pattern is employed to deal with the hyperspectral data and extract the texture features of the hyperspectral remote sensing image. The multivariate logistic regression model is used to select the unlabeled samples with the largest amount of information, and the unlabeled samples with neighborhood information and priority classifier tags are selected to obtain the pseudo-labeled samples after learning. The problem of limited labeled samples of hyperspectral images is solved. The data of Indian

*Pines, Salinas scene and Pavia University are selected in here. The experiment results of the BT method are obviously better than those of other methods. The block window of Indian Pines dataset is 7*7. The block windows of Pavia University and Salinas scene are 25 * 25 and 20 * 20, respectively. The combination of MLR and SRC can get better classification results. The obtained classification results by the classifier and the labeled samples are smoother and has fewer discrete points, which indicates that the generalization ability of the classifier is improved by labeling the samples from the classification visualization. For Indian Pines data, the classification results of AA, OA and KAPPA are 84.7%, 94.42% and 0.914, respectively. For Pavia University data, the classification results of AA, OA and KAPPA are 81.87%, 88.53% and 0.848, respectively. For Salinas Scene data, the classification results of AA, OA and KAPPA are 87.76%, 92.64% and 0.918, respectively. Therefore, the classification method obtains the higher classification accuracy.*

However, the proposed classification method has the more computing time, so the next step should be more in-depth research to reduce the time complexity.

And so on, please read our revised manuscript. We thank the comments and the opportunity for us to improve our manuscript. As much as possible, the questions were taken into account during the preparation of the revised manuscript. We hope that the manuscript is now suitable for publication.