Comments on "Partial-Volume Bayesian Classification of Material Mixtures in MR Volume Data Using Voxel Histograms"

Hamid Soltanian-Zadeh* and Joe P. Windham

***Index Terms*— Eigenimage filtering, magnetic resonance imaging (MRI), partial volume estimation.**

We read with interest, the above paper.[1] The methods the authors presented are interesting and illustrate the significance of partial volume information in medical image analysis. However, they seem to be unaware of the details of the literature on *optimal* partial volume estimation from MRI [1]–[3], although they cite one of the references. As such, there are a few important points that the authors did not describe correctly. The purpose of this communications is to explain these points.

1) The *optimal* (unbiased minimum variance) estimator for the conditions assumed [including linearity of magnetic resonance imaging (MRI) gray levels for the partial volume voxels] is the eigenimage filtering method [2], [3]. Nonlinear estimators are not optimal for linear models. It is true that nonlinear estimators are more flexible, but this flexibility fits the nonlinear model into the observation noise when the original physical model has in fact been *linear*, resulting in a *suboptimal* estimation.
2) What is really important in many medical image analysis applications is the total volume of the objects in the scene, not the partial volumes in individual voxels. The linear solution generated by the eigenimage filter results *zero mean* noise in voxel partial volume estimates. Therefore, the sum of the partial volume estimates (which generates the total volume of the desired object) converges to the true volume as the number of the voxels belonging to the object increases.
3) If the appearance of the segmented object is important (for instance for visualization purposes), then the nonlinear edge-preserving noise suppressing filter we developed and presented in [4] can be used before the eigenimage filtering to use spatial information and improve the appearance of the image while preserving partial volume information on average.
4) The conclusion Laidlaw *et al.* made in the beginning of Section IX in the above paper,[1] indicating that the new method is more accurate than existing methods in many cases, is neither mathematically proved nor experimentally illustrated. In contrast, we have mathematically proved and experimentally illustrated the optimality of the estimates provided by the eigenimage filter in [2], [3].

In conclusion, while the method of Laidlaw *et al.* in the above paper[1] is interesting and may prove useful in certain situations, it is not *optimal* for partial volume estimations and volume calculations when multiple MR images of the same anatomical site are available. In most clinical situations, T1-, T2-, and proton-density-weighted images are acquired for each anatomical section. Utilizing this data, the optimal partial volume estimates may be obtained by the eigenimage filter.

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*H. Soltanian-Zadeh is with the Image Analysis Lab., Department of Radiology, Henry Ford Health System, Detroit, MI 48202 USA. He is also with the Department of Radiology, Case Western Reserve University, Cleveland, OH 44106 USA and the Department of Electrical and Computer Engineering, The University of Tehran, Tehran 14399, Iran (e-mail: hamids@rad.hfh.edu).

J. P. Windham is with the Image Analysis Lab., Department of Radiology, Henry Ford Health System, Detroit, MI 48202 USA.

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Author's Reply

David H. Laidlaw

***Index Terms*—Bayesian probability theory, biomedical signal processing, discrete signal processing, feature extraction, functional analysis, geometric modeling, image processing, partial volume, mixed modeling and estimation, multiscale analysis, multidimensional signal processing, multispectral classification, multivariate segmentation, tissue classification, volume measurement.**

The concept of optimality always rests on a framework of assumptions. Eigenimage filtering is optimal under a certain set of assumptions. However, our voxel histogram method uses different assumptions and, as we demonstrate, produces better results with fewer images. In this communication we first discuss some of the assumptions leading to the eigenimage filtering method, then describe how our assumptions differ and how they lead to a different type of classification method. We then present results comparing the two methods, address the four points raised in the above communication and state our conclusions.

As Dr. Soltanian-Zadeh and Dr. Windham point out in their "comments," they have proven the optimality of the eigenimage filtering method [1], [2] for preserving some features within multiple spatially correlated single-valued images while suppressing other features. They find the linear combination of images that best accomplishes their goals.

Eigenimage filtering has a number of advantages. First, it preserves partial-volume effects so that resulting image combinations have appropriately sampled boundaries. Second, it produces the unique linear

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The author is with the Department of Computer Science, Box 1910, Brown University, Providence, RI 02912 USA (e-mail: dhl@cs.brown.edu).

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TABLE I

COMPARISON OF OUR VOXEL HISTOGRAM CLASSIFICATION WITH EIGENIMAGE FILTERING FOR VOXELS HAVING NO PARTIAL VOLUME EFFECTS. DESIRED SIGNATURES SHOULD BE MAPPED TO 1.0 AND UNDESIRED SIGNATURES TO 0.0. NOTE THAT THE VOXEL HISTOGRAM CLASSIFICATION HAS CONSISTENTLY SMALLER STANDARD DEVIATIONS—THE EIGENIMAGE-FILTERED IMAGES HAVE NOISE LEVELS 2–4 TIMES HIGHER DESPITE HAVING ADDITIONAL IMAGE DATA

		eigenimage filtering (three-valued data)		voxel histogram (two-valued data)	
		mean	standard deviation	mean	standard deviation
desired signatures	Material 1	1.0113	0.241	0.9946	0.064
	Material 2	0.9989	0.124	0.9926	0.077
	Background	0.9986	0.113	0.9976	0.038
undesired signatures	Material 1	−0.0039	0.240	0.0013	0.017
	Material 2	−0.0006	0.100	0.0002	0.004
	Background	0.0016	0.117	0.0065	0.027

combination of images that best satisfies their unbiased minimum variance metric. Third, it is computationally very quick to compute a solution and very quick to apply it to a set of images.

Their method relies on a number of assumptions. The most significant is the assumption that all information useful for classification of a point is contained in the vector-valued sample value at that point. This assumption does not take into account the spatial juxtaposition of neighboring measurements. Our method demonstrates that the relationship among nearby measurements contains information that can greatly improve classification results. The assumption that operations must be done directly to the sample values leads to the conclusion that linear combinations of images are an optimal classification method.

Our voxel histogram method[1] starts from a different assumption. We assume that the original samples are point samples of a band-limited continuous function. From the samples we can reconstruct the continuous function. We then look at all the values the function takes on in a small region near a sample point and use the information to determine how much of each material is contained in that small region.

The simulated data that we used as an example in our paper[1] was two-valued. The images contained three materials with the following signatures: (1000, 600), (4000, 3800), and (2000, 800). Noise was additive and normally distributed with a standard deviation of (128, 160). Our voxel-histogram method created three new images from the two starting ones. Each image retained the signal contribution for one material while suppressing signal contributions for the other two. The resulting images not only visually identified the expected regions, they also yielded low rms error, as we described in our paper.

The human brain slice data that we used was also two-valued. Within it we identified six material signatures. Our method created six images, each of which retained signal from one material and suppressed signal from the other five materials.

Our understanding of the eigenimage filtering method is that, in general, it cannot suppress signal from two materials and retain it from a third using the simulated two-valued data of our example. It would also be unable to replicate our results that differentiate six materials in two-valued data. To compare our results with eigenimage filtering we created a third simulated dataset and combined it with the two-valued data from our earlier work. The resulting images have three-valued signatures of (1000, 600, 250), (4000, 3800, 3400), and (2000, 800, 1200). The standard deviation of the noise added to the third dataset was 160. We used the eigentool software package[2] to perform eigenimage filtering of the three-valued data. Comparative

[2] "Eigentool," acquired from Henry Ford Hospital, Diagnostic Rediology and Medical Imaging, Image Analysis Lab, Detroit, MI, via e-mail to: L. Bower, lubieb@rad.hfh.edu.

TABLE II

COMPARISON OF TOTAL VOLUME CALCULATIONS USING BOTH ALGORITHMS. BOTH ALGORITHMS PERFORM ROUGHLY EQUIVALENTLY, EACH DOING SOMEWHAT BETTER FOR SOME MATERIALS THAN OTHERS. NOTE THAT THE EIGENIMAGE FILTERING WAS PERFORMED ON THREE-VALUES DATA, WHILE THE VOXEL HISTOGRAM CLASSIFICATION USED ONLY TWO-VALUED DATA

	Volume Measurement Error	
	eigenimage filtering (three-valued data)	volume histogram (two-valued data
Material 1	−0.021%	0.004%
Material 2	0.266%	−0.452%
Background	−0.164%	0.146%

TABLE III

COMPARISON OF RMS ERROR FOR BOTH ALGORITHMS. RMS ERROR WAS CALCULATED FOR THE REGION WHERE PARTIAL VOLUME MIXING WAS OCCURRING, I.E., NEAR MATERIAL BOUNDARIES. ERROR FOR THE EIGENIMAGE FILTERING CASE IS TWO TO FOUR TIMES HIGHER DESPITE THE ADDITIONAL IMAGE DATA AVAILABLE TO IT

	eigenimage filtering (three-valued data)	volume histogram (two-valued data)
Material 1	0.241	0.056
Material 2	0.098	0.037
Background	0.117	0.056

results are shown in Tables I–III. In these tables we see that voxel histogram classification produced results with lower noise levels, lower rms error, and comparable volume measurement accuracy compared to the results produced by eigenimage filtering.

In their comments, Dr. Soltanian-Zadeh and Dr. Windham raised four main points that we would like to address.

1) Optimality: Both our voxel-histogram method and the eigenimage filtering method implement an optimization. Hence, they are "optimal" by construction. Each uses a different metric for optimality, and so comparisons other than a proof of optimality are required. In our paper,[1] we compared the voxel-histogram method with some other methods. Our accuracy measures were relative rms error improvement over a naive probabilistic classification algorithm and accuracy of total volume measurements. We chose not to compare our method with the eigenimage filtering method directly because eigenimage filteringseemed restricted to cases where larger numbers of images were available.

2) Total Volume: While for some applications total volume measurements are the most useful measurement, for other applications they are not. In our application, partial volume accuracy at a voxel level is more important. Without that accuracy, geometric boundary models extracted from the classified data will not be locally accurate. rms error is a more meaningful metric.

3) Improving Appearance: The use of a nonlinear noise-reducing filter followed by eigenimage filtering may be appropriate for improving the appearance of extracted models in some situations. Our goal in making models is to improve their accuracy, not to improve their appearance. We address the accuracy issue by modeling the partial volume effects created by the sampling process near boundaries and using that to more accurately extract material information. We believe that the suggested alternative is a less effective solution for our purposes. It loses detail in the resulting images and it does not preserve partial volume effects, since it is a nonlinear filter applied to the sample values.

4) A Counterexample: Our voxel-histogram method works in cases where eigenimage filtering cannot produce a meaningful answer. In a simple test case with two-valued data and three materials eigenimage filtering does not directly apply. Even with the addition of a third data image for eigenimage filtering, results show that our voxel histogram method produces lower rms error rates, comparable volume measurement error, and lower variance.

The eigenimage filtering method is elegant, efficient, and applicable to many classification problems. However, our approach of reconstructing a continuous function from sampled data and examining the function over regions suggests new types of classification methods. These new methods are nonlinear with respect to the individual sample values but they do correctly account for the linearity of signal juxtaposition and additive noise.

In our paper[1] we stated, "linear operations are not as flexible as nonlinear operations, and so either more data must be acquired or classification results will not be as accurate," in reference to the eigenimage filtering methods. We hope that this expansion on that brief statement helps to clarify our meaning.

References

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