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**Gilson Alexandre Ostwald Pedro da Costa**

**A Knowledge-Based Approach for Automatic Interpretation  
of Multisate Remote Sensing Data**

**Tese de Doutorado**

Thesis presented to the Postgraduate Program in  
Electrical Engineering of the Departamento de  
Engenharia Elétrica, PUC-Rio as partial fulfillment of  
the requirements for the degree of Doutor em  
Engenharia Elétrica.

Advisor: Raul Queiroz Feitosa

Rio de Janeiro  
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**Raul Queiroz Feitosa**

Advisor

Pontifícia Universidade Católica do Rio de Janeiro (PUC-Rio)

**Gilberto Câmara Neto**

Instituto Nacional de Pesquisas Espaciais (INPE)

**Bruno Feijó**

Pontifícia Universidade Católica do Rio de Janeiro (PUC-Rio)

**Christian Heipke**

Leibniz Universität Hannover

**Antonio Maria Garcia Tommaselli**

Universidade Estadual Paulista (UNESP)

**Marley Maria Bernardes Rebuzzi Vellasco**

Pontifícia Universidade Católica do Rio de Janeiro (PUC-Rio)

**José Eugênio Leal**

Coordinator of the Centro Técnico Científico da PUC-Rio

Rio de Janeiro  
March 2nd, 2009

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### **Gilson Alexandre Ostwald Pedro da Costa**

Graduated in Computer Engineering at the Pontifícia Universidade Católica do Rio de Janeiro (PUC-Rio) in 1991, having specialized professionally in the development of geographic information systems and remote sensing applications. Obtained the degree of Mestre, in Computer Engineering with emphasis on Geomatics, at the Universidade do Estado do Rio de Janeiro (UERJ) in 2003. Since then has worked in the field of remote sensing image analysis.

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## Resumo

Costa, Gilson Alexandre Ostwald Pedro da; Feitosa, Raul Queiroz. **Uma Abordagem Baseada em Conhecimento para a Interpretação Automática de Dados de Sensoriamento Remoto Multi-Data**. Rio de Janeiro, 2009, 149p. Tese de Doutorado – Departamento de Engenharia Elétrica, Pontifícia Universidade Católica do Rio de Janeiro.

O objetivo genérico desta Tese foi o desenvolvimento de técnicas computacionais baseadas em conhecimento para apoiar a interpretação automática de dados de sensoriamento remoto multi-temporais, com ênfase na investigação da aquisição e representação explícita de conhecimento temporal, bem como na sua integração com outros tipos de conhecimento dentro do processo de interpretação. Dois objetivos específicos, inter-relacionados, foram perseguidos: (i) o desenvolvimento de um novo método de classificação baseado no conceito de cadeias nebulosas de Markov (CNM), que provê meios para a estimação de seus parâmetros temporais e para a utilização de conhecimento temporal no processo de classificação; e (ii) a modelagem e implementação de um ambiente baseado em conhecimento, de código livre, para a interpretação de dados de sensoriamento remoto. Para validar o novo método de classificação multi-temporal, foram realizados experimentos voltados à interpretação de uma sequência de três imagens LANDSAT de uma área na Região Centro-Oeste do Brasil, utilizando um método estocástico e outro analítico para a estimação das matrizes de transição de classes que compõem o modelo CNM. Enquanto os classificadores mono-temporais obtiveram uma acurácia média por classe de 55%, o esquema multi-temporal alcançou acurácias entre 63% e 94%. Resultados semelhantes em termos de acurácia global foram verificados. Além disso, quando comparado a abordagens multi-temporais correlatas, o método proposto obteve melhores resultados. De forma a validar o ambiente baseado em conhecimento aqui proposto, o método CNM foi implementado através de suas funcionalidades. Um conjunto de experimentos nos quais diferentes variações do método CNM, estruturadas no novo ambiente, foi executado satisfatoriamente.

## Palavras-chave

Processamento digital de imagens; Interpretação baseada em conhecimento; Imagens multi-temporais; Sensoriamento Remoto; Cadeias nebulosas de Markov.

## Abstract

Costa, Gilson Alexandre Ostwald Pedro da; Feitosa, Raul Queiroz (Advisor). **A Knowledge-Based Approach for Automatic Interpretation of Multidate Remote Sensing Data**. Rio de Janeiro, 2009, 149p. PhD Thesis – Departamento de Engenharia Elétrica, Pontifícia Universidade Católica do Rio de Janeiro.

The general objective of this research was the development of knowledge-based computational techniques to support the interpretation of multitemporal remote sensing data, focusing on the investigation of the explicit representation of temporal knowledge and its integration to other types of knowledge; and also on the processing and acquisition of temporal knowledge. Two interrelated, specific objectives were pursued: (i) the development of a novel multitemporal classification method based on the concept of fuzzy Markov chain (FMC) that provides for the automatic estimation of its temporal related parameters and for the exploration of temporal knowledge in the classification process; and (ii) the design and implementation of an open-source, knowledge-based framework for multitemporal interpretation of remote sensing data. In order to validate the new multitemporal classification method, experiments were carried out aiming at the interpretation of a sequence of three LANDSAT images from the central region of Brazil, using both a stochastic and an analytical technique to estimate the class transition possibilities that compose the FMC model. While the monotemporal classifiers used in the experiments attained an average class accuracy of approximately 55%, the multitemporal scheme reached accuracies between 65% and 94%. Similar results in terms of overall accuracy were also observed. Furthermore, when compared to two alternative multitemporal classification approaches, the devised method consistently showed better results. In order to validate the proposed multitemporal framework, the FCM-based method was implemented using its temporal functionalities, and a number of experiments in which different variants of the FCM-based method were structured through the framework were successfully carried out.

## Keywords

Digital image processing; Knowledge-based image interpretation; Multitemporal image classification; Remote sensing; Fuzzy Markov chains.

## Table of contents

1. Introduction	16
1.1. Objectives of the thesis	21
1.2. Organization of the remainder of the thesis	22
2. Previous works	23
2.1. Knowledge-based image interpretation	23
2.1.1. Definition of knowledge	25
2.1.2. Semantic network-based systems	27
2.1.3. Systems based on frames	32
2.1.4. Rule-based systems	33
2.1.5. Procedural interpretation	34
2.1.6. Multitemporal interpretation	35
2.1.7. Control strategies	37
2.2. Multitemporal interpretation methods	39
2.2.1. Cascade multitemporal approaches	41
2.2.2. Semantic approaches	42
3. A novel multitemporal cascade-classification method	44
3.1. Fuzzy Markov chains	45
3.2. Problem statement	47
3.3. General classification model	48
3.4. Particularization of the classification model	51
3.5. Estimating transition possibilities	54
3.5.1. Accuracy functions	55
3.5.2. Estimation techniques	57
4. Evaluation of the proposed multitemporal classification method	61
4.1. Description of the data set	61
4.1.1. Segmentation procedure	62
4.1.2. Validation data	63
4.2. Monotemporal classifier design	66



4.3. Multitemporal classifier design	68
4.4. Estimation procedures	69
4.5. Experimental results	70
4.5.1. Transition possibilities estimated on the average class accuracy	71
4.5.2. Transition possibilities estimated on the overall accuracy	80
4.5.3. Comparison to alternative approaches	87
5. A knowledge-based framework for multitemporal image interpretation	92
5.1. GeoAIDA overview	95
5.1.1. Knowledge representation	96
5.1.2. Top-down operators	97
5.1.3. Bottom-up operators	98
5.1.4. Interpretation control	99
5.1.5. Implementation of the control mechanism	102
5.2. Multitemporal extension of InterIMAGE	104
5.2.1. Temporal knowledge representation	104
5.2.2. Control process	106
5.2.3. Temporal top-down operator	111
5.2.4. Temporal bottom-up operator	112
6. Implementation of the proposed multitemporal classification method in the multitemporal framework	114
6.1. 6.1. Description of the operators	114
6.1.1. Structural operators	115
6.1.2. Temporal operators	117
6.1.3. Implementation of the operators	120
6.2. Experimental results	123
6.2.1. Sequential interpretation experiments	123
6.2.2. Synchronous interpretation experiments	128
7. Conclusions and directions for future research	135
References	139
Appendix A. Finite state machine with temporal states	146

## List of figures

Figure 1. Semantic network in the ERNEST system (Niemann et al., 1990).	28
Figure 2. Semantic network in the AIDA system (Liedtke et al., 1997).	29
Figure 3. Semantic network in the GEOAIDA system (Liedtke et al., 2001).	29
Figure 4. A judgment procedure in GeoAIDA.	30
Figure 5. A class hierarchy in the Definiens Developer software: inheritance network (left) and groups network (right).	31
Figure 6. A class description in the Definiens Developer software (left) and of a membership function (right).	32
Figure 7. A process tree in the Definiens Developer software.	35
Figure 8. Semantic network with temporal relations in the AIDA system (Liedtke and Grawe, 2001).	36
Figure 9. Class transition diagram in the method proposed in (Pakzad, 2002).	37
Figure 10. Class transition diagram.	46
Figure 11. The <i>forward</i> multitemporal classification model.	50
Figure 12. The <i>backward</i> multitemporal classification model.	50
Figure 13. Algorithm for determining the classes of an image object at times $t$ and $t+1$ (argument $n$ represents the total number of classes).	53
Figure 14. Plot of the $\text{sig}(ax)$ function for $a=10$ .	58
Figure 15. Taquari River sub-basin.	62
Figure 16. Segmentation procedure result.	63
Figure 17. Reference segments and videography flight line. Adapted from (Mota, 2004).	64
Figure 18. Classes assigned to the reference segments in each year: top 1999, center 2000, bottom 2001.	65
Figure 19. Membership function for fuzzy set short.	67
Figure 20. Class transition diagram for the test area.	69
Figure 21. The monotemporal classifiers used as benchmark in the	

performance analysis.	71
Figure 22. Typical results for the classification of the 1999 image: top, monotemporal; center multitemporal with fuzzy classifier for later date; bottom multitemporal with ideal classifier for later date (average class accuracies: 64%, 79% and 95%, respectively).	77
Figure 23. Typical results for the classification of the 2000 image: top, monotemporal; center multitemporal with fuzzy classifier for earlier date; bottom multitemporal with ideal classifier for earlier date (average class accuracies: 60%, 67% and 96%, respectively).	78
Figure 24. Typical results for the classification of the 2001 image: top, monotemporal; center multitemporal with fuzzy classifier for earlier date; bottom multitemporal with ideal classifier for earlier date (average class accuracies: 58%, 71% and 94%, respectively).	79
Figure 25. Typical results for the classification of the 1999 image: top, monotemporal; center multitemporal with fuzzy classifier for later date; bottom multitemporal with ideal classifier for later date (overall accuracies: 53%, 76% and 96%, respectively).	84
Figure 26. Typical results for the classification of the 2000 image: top, monotemporal; center multitemporal with fuzzy classifier for earlier date; bottom multitemporal with ideal classifier for earlier date (overall accuracies: 62%, 86% and 95%, respectively).	85
Figure 27. Typical results for the classification of the 2001 image: top, monotemporal; center multitemporal with fuzzy classifier for earlier date; bottom multitemporal with ideal classifier for earlier date (overall accuracies: 59%, 87% and 94%, respectively).	86
Figure 28. Maximum jointly decision fusion multitemporal classifier for two dates (TP-LIK).	88
Figure 29. Two date classification fusion using a neural network.	88
Figure 30. Structural and temporal dimensions of a multitemporal interpretation problem.	94
Figure 31. Components of the analysis process. Adapted from (Pahl, 2003).	95
Figure 32. Attributes of a node of the semantic network in GeoAIDA.	97

Figure 33. Interpretation process flow. Adapted from (Pahl, 2003).	101
Figure 34. Different semantic networks for different points in time.	105
Figure 35. Representing the multitemporal interpretation knowledge model through a single semantic network with temporal nodes.	105
Figure 36. Flow of control in sequential multitemporal interpretation.	110
Figure 37. Flow of control in synchronous multitemporal interpretation.	111
Figure 38. Land-cover multitemporal interpretation problem, $\omega_i$ correspond to land cover classes.	115
Figure 39. Placement of the structural monotemporal top-down operators in the land-cover classification knowledge models.	117
Figure 40. Placement of the temporal operators in the land-cover classification knowledge models.	120
Figure 41. Overlapping regions of hypotheses from different times.	121
Figure 42. Possible outcome of the multitemporal Merge routine.	122
Figure 43. Semantic network for sequential classification of the image from 1999.	124
Figure 44. Reference classification for the 1999 image.	126
Figure 45. Classification of the reference segments over the 1999 image: top, sequential classification – true classification for 2000 not known; bottom, sequential classification – true classification for 2000 known (average class accuracies: 69.6 % and 96.4%, respectively).	127
Figure 46. Semantic network for synchronous classification of the images from 2000 and 2001.	128
Figure 47. Classification of the reference segments over the 2000 image: top, reference classification; bottom, synchronous classification – true classification for 2001 not known (average class accuracy of 75.6%).	130
Figure 48. Classification of the reference segments over the 2001 image: top, reference classification; bottom, synchronous classification – true classification for 2000 not known (average class accuracy of 73.4%).	131
Figure 49. Top, synchronous classification for the reference segments of the 2001 image – true classification for 2000 known (average class	

accuracy of 96.1%); bottom, complete classification of the 2001 image  
– true classification of the reference segments in 2000 known. 133

## List of tables

Table 1. Geographical limits of the images used in the experiments.	61
Table 2. Land cover classes considered in the experiments and number of reference segments in each year.	64
Table 3. Class transitions from 1999 to 2000.	66
Table 4. Class transitions from 2000 to 2001.	66
Table 5. Rule base of the monotemporal classifier.	68
Table 6. Average class accuracy for both dates (averages over 100 experiments).	72
Table 7. Average class accuracy for both dates (average over 100 experiments) using an ideal classifier at the earlier date.	72
Table 8. Average class accuracy for both dates (average over 100 experiments) using an ideal classifier at the later date.	73
Table 9. Confusion matrix for the monotemporal classifier for the image from 2001.	75
Table 10. Confusion matrix for the multitemporal classifier for the image from 2001, using average class accuracy and the LS-based method for transition matrix estimation – prior classification not known.	75
Table 11. Confusion matrix for the multitemporal classifier for the image from 2001, using average class accuracy and the LS-based method for transition matrix estimation – prior classification known.	75
Table 12. Overall accuracy for both dates (averages over 100 experiments).	81
Table 13. Overall accuracy for both dates (average over 100 experiments) using an ideal classifier at the earlier or later dates.	82
Table 14. Confusion matrix for the multitemporal classifier for the image from 2001, using overall accuracy and the LS-based method for transition matrix estimation – prior classification not known.	82
Table 15. Confusion matrix for the multitemporal classifier for the image from 2001, using overall accuracy and the LS-based method for transition matrix estimation – prior classification known.	82

Table 16. Performance comparison of the monotemporal and three multitemporal approaches: the proposed method FCM with its two parameter estimation techniques LS and GA; the maximum jointly decision fusion likelihood (TP-LIK), and the neural network method (NN).	89
Table 17. Performance comparison of the monotemporal classification with the proposed FCM method using three different parameter estimation techniques: GA-FW, LS and GA.	91
Table 18. Confusion matrix for the sequential classification of the image from 1999 – classification from 2000 not known.	125
Table 19. Confusion matrix for the sequential classification of the image from 1999 – classification from 2000 known.	126
Table 20. Confusion matrix for the synchronous classification of the image from 2000 – classification from 2001 not known.	132
Table 21. Confusion matrix for the synchronous classification of the image from 2001 – classification from 2000 not known.	132
Table 22. Confusion matrix for the synchronous classification of the image from 2001 – classification from 2000 known.	134