Cyclostationary signal sensing algorithm based on principal component analysis and AdaBoost

Wei Qin*
School of Information Engineering, Shenyang Polytechnic College,2238552865@qq.com

ABSTRACT

At present, with the development of 5G technology, the bandwidth requirement of data communication is increasing, which makes the limited spectrum resources become more and more tight. Based on the current situation of the utilization and allocation of radio spectrum resources, the unused frequency bands have become less and less, and the shortage of radio spectrum resources is very serious. In this paper, a spectrum sensing algorithm based on principal component analysis (PCA) and AdaBoost is proposed to solve the problem of low detection rate of main user signal in wireless channel environment. Firstly, we extract the feature parameters of the signal by using the cyclostationary PCA algorithm, obtain the principal components of the signal, generate the samples, and construct the sample set, then the AdaBoost algorithm is used to classify and detect the signals in the presence and absence of the main user. The simulation results show that the proposed algorithm has better classification and detection performance compared with the artificial neural network and the max-min eigenvalue algorithm under low signal-to-noise ratio, the sensing of primary user signal is realized effectively.

CCS CONCEPTS

• **Information systems**; • **Mobile information processing systems**;

KEYWORDS

cognitive network, principal component analysis, AdaBoost, spectrum sensing

ACM Reference Format:
Wei Qin. 2023. Cyclostationary signal sensing algorithm based on principal component analysis and AdaBoost. In *The 15th International Conference on Digital Image Processing (ICDIP 2023), May 19–22, 2023, Nanjing, China.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3604078.3604110

1 INTRODUCTION

With the rapid development of modern wireless communication technology, the contradiction between the existing spectrum resources and the increasing spectrum demand is deepening day by day. The efficient utilization of spectrum resources and the reduction of spectrum waste have become the focus to be solved urgently. In view of the contradiction between the shortage of spectrum resources and the serious underutilization of frequency bands, many scholars and experts at home and abroad began to consider how to make more effective use of the existing spectrum resources. Based on this idea, the original conception of Cognitive Networks (CN) is proposed [1–4].In December 2003, the FCC issued a decree, "Any terminal device with cognitive wireless network capabilities shall be allowed to use a particular wireless licensed band even without permission if it finds that the band is not occupied in the time or space domain, "The proposal of this bill has laid a good legal foundation for the new wireless spectrum resource utilization technology. In May 2004, the FCC issued another announcement, which proposed the use of cognitive technology to implement the Open Spectrum System (OSS). The Nautilus project was Microsoft Research Asia by a team led by Professor Haitao Zheng of the University of California, Santa Barbara (UCSB). Many valuable researches have been carried out in the fields of dynamic spectrum allocation, access and auction in cognitive networks, and some highly applicable techniques and methods have been proposed. In addition, the University of California, Berkeley, Georgia Institute of Technology, University of Illinois at Urbana–Champaign, Massachusetts Institute of Technology, the University of Southern California and other scientific research institutions are also active in cognitive network-related technology research. In 2009, the National Natural Fund Committee (NSFC) funded research on cognitive network technologies in key areas, including CR-based industrial wireless network design theory and optimization methods and wireless spectrum environmental cognition theory [5–7]. The"863" plan is a key project in the field of information technology. It plans to invest 40 million yuan by the end of 2010 in the research and development of "Spectrum resource sharing wireless communication system". In addition, the University of Electronic Science and technology has collaborated with Chinese Huawei Technologies Co. Ltd. to participate in the IEEE's activities on the standardization of cognitive radio and has submitted two research proposals to the IEEE 802.22 Working Group. In addition, the Hong Kong University of Science and Technology, Tsinghua University, Southeast University, Harbin Institute of Technology, Beijing University of Posts and Telecommunications, Xidian University and Xi'an Jiaotong University have also conducted research on cognitive network technologies [8–10].

As the foundation and core of cognitive network technology, Spectrum Sensing has become a research hotspot for its fast, effective and accurate sensing detection of primary users. In order to solve this problem effectively, many new communication technologies and methods have been studied. At present, the common

*Corresponding author.

ICDIP 2023, May 19–22, 2023, Nanjing, China

ACM ISBN 979-8-4007-0823-7/23/05…$15.00
https://doi.org/10.1145/3604078.3604110

spectrum sensing algorithms include energy detection, cyclostationary feature detection and matched filter detection [11]. The energy detection algorithm has the advantages of no prior information of the main user signal, flexible implementation, and can be applied to the sensing of different center frequencies and bandwidth. The matched filter detection method has good matched filter characteristics, but it needs to obtain the prior information of the main user signal, otherwise it cannot sense the main user effectively. Cyclostationary feature detection method has strong anti-noise performance, but the algorithm has a large amount of computation, long perception time [12, 13].

On this basis, the spectrum sensing problem of the main user signal under the condition of low SNR is further studied. In literature [14]and [15], the maximum-minimum eigenvalue(Mme) method is proposed by using the eigenvalues of the received signal matrix to study the main user signal detection under different signal-to-noise ratios Literature [16] adopts machine learning method to solve the spectrum sensing problem under a certain signal-to-noise ratio environment; literature [17] applies SVM algorithm to cognitive network environment; This paper proposes a method for classifying and perceiving primary user signals in a Additive white Gaussian noise environment using Support vector machine. The above algorithms have made some achievements in spectrum sensing of main user signal, but the effect is not obvious in low SNR environment.

For these reasons, a spectrum sensing algorithm based on cyclostationary feature principal component analysis (PCA) and AdaBoost is proposed in this paper. The main contributions of this paper are as follows:

The system model is introduced in Section 2.Section 3 introduces the spectrum sensing algorithm of cyclostationary signal based on PCA and AdaBoost. Simulation and analysis are described in in Section 4.Section 5 summarizes the main conclusions of this paper.

2 SYSTEM MODEL

In this paper, the traditional multi-user cooperative spectrum sensing model is adopted. Each secondary user perceives the information of the primary user, and uses the fusion mechanism to fuse the information, and finally transmits it to the data center. According to the spectrum sensing characteristics of the main user signal in cognitive network environment, there are W main users and G secondary users, and each main user signal does not interfere with each other. For any sub-user, the system model can be summed up as a binary model.

$$\begin{cases} H_0 : y(t) = n(t) \\ H_1 : y(t) = \sum\limits_{w=1}^{W} s_w(t) + n(t) \end{cases} \tag{1}$$

Among them, H_0 for the no main user situation, H_1 for the main user situation, $0 \le t \le T$,T for the receiving signal sampling time. Sw(t) is a primary user signal, n(t) with a mean value of zero and a variance σ_n^2 of Additive white Gaussian noise.

3 SPECTRUM SENSING ALGORITHM OF CYCLOSTATIONARY SIGNAL BASED ON PCA AND ADABOOST

3.1 PCA algorithm

Principal Component Analysis (PCA), also known as K-L transform, is an effective feature extraction method for analyzing data in statistics, the basic idea is to select a few new variables which can best reflect the information of the original variables in the large input space through linear transformation form [18]. As a classical method in multivariate statistical analysis, principal component analysis has been paid more and more attention by researchers, and widely used in image processing, signal processing, pattern recognition, communication and other fields.

Under the model of cognitive network system, the steps of dimensionality reduction and feature extraction using PCA are as follows.

Set $h_{l1}, h_{l2}, \cdots, h_{lM}$ said M a $\alpha \neq 0$ $\tilde{S}^{\alpha}(f)$ value, and with the original sample matrix $H = (h_{lm})_{M\times L}$, $l = 1, 2, \cdots, L,\ m = 1, 2, \cdots, M$,among them,$l$ for sample,m for dimension.

Step 1.Standardization of the original sample parameters.

Set to represent the result of standardization of the original sample parameters

$$x_{lm} = \frac{h_{lm} - \overline{h_m}}{S_m} \tag{2}$$

Formula:$\overline{h_m} = \frac{1}{L}\sum\limits_{l=1}^{L} h_{lm}$, $S_m = \sqrt{\frac{\sum_{l=1}^{L}(h_{lm}-\overline{h_m})^2}{L-1}}$ respectively, the mean and standard deviation of the original sample parameters, then constitute a standardized sample parameter set for $X = [X_1, X_2, \cdots X_l], X_l = [x_{l1}, x_{l2}, \cdots, x_{lM}]^T \in R^M$, $l = 1, 2, \cdots, L$.

Step 2. Calculate the covariance matrix of the standardized sample parameter set

$$C = E[XX^T] \tag{3}$$

Step 3.Calculate the eigenvalues of the covariance matrix $\lambda_1 \ge \lambda_2 \ge \cdots \ge \lambda_M$ C and their corresponding eigenvectors $U_1, U_2, \cdots, U_M$

$$CU_l = \lambda_m U_l; \quad m = 1, 2, \cdots, M \tag{4}$$

Step 4. Calculate the variance contribution rate and select the principal component

$$\phi(K) = \frac{\sum\limits_{k=1}^{K}\lambda_k}{\sum\limits_{m=1}^{M}\lambda_m} > threshold \tag{5}$$

K said variance contribution rate, $threshold \ge 0.85$, $k = 1, 2, \cdots, K$, the value obtained K from formula (5) .

Set of y_{lk} is after the dimension reduction feature vectors Y_l first k principal component, by the formula (6) the y_{lk} value can be obtained.

$$Y_l = X_l^T U = [y_{l1}, y_{l2}, \cdots, y_{lK}] \tag{6}$$

Of the ordinance, $U = [U_1, U_2, \cdots, U_K]$.

3.2 AdaBoost algorithm

AdaBoost algorithm is a machine learning method based on classifier proposed by Freund et al.in 1997.The basic idea of this algorithm is to stack a large number of weak classifiers with general classification ability by a certain method to form a strong classifier with strong classification ability, furthermore, a more accurate classification and detection of the samples to be tested is realized [19].The algorithm steps are as follows:

The weight of the sample is normalized in step 1.

Step 1 construct a weak classifier. A weak classifier is defined as the optimal threshold for each feature of all samples after the weights of the samples are determined.

$$h_j(x) = \begin{cases} 1, & p_j f_j(x) \prec p_j\theta_j \\ 0, & otherwise \end{cases} \tag{7}$$

$h_j(x)$ for weak classifier to sample the output value of x ,p_j for the inequality sign direction bias (value of plus or minus 1),θ_j the threshold value,f_j sample rectangular characteristic value of x.

Step 2 determines the optimal weak classifier. After constructing the weak classifier, the error function of each feature is calculated for all samples

$$\varepsilon_j = \sum_{j=1}^{n} \omega_{t,j} \left| h_j(x_i) - y_i \right| \tag{8}$$

Minimize its objective function. Among them, the classifier with the smallest ε_j is chosen as the best weak classifier of the training.

Step 4 updates the corresponding weights for each sample. In the whole training process, the weights of the correctly classified samples decrease, while the weights of the wrongly classified samples increase, which makes the misclassified samples get more attention after each round of training, and then improve the final classification accuracy. Sample weight $\omega_{t+1,j} = \omega_{t,j}\beta_t^{1-e_j}$, where $\beta_t = \varepsilon_t/(1-\varepsilon_t)$, if the first j sample x_j is correctly classified $e_j = 0$, otherwise $e_j = 1$.

Step 5 after several rounds of training, a strong classifier composed of several weak classifiers is obtained.

$$H(x) = \begin{cases} 1, & \sum\limits_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2}\sum\limits_{t=1}^{T} \alpha_t \\ 0, & otherwise \end{cases} \tag{9}$$

Of the form, $\alpha_t = \ln \frac{1-\varepsilon_t}{\varepsilon_t}$.

3.3 The procedure of spectrum sensing algorithm

A new training sample set and test sample set are generated according to the feature vectors Y_l^0 and Y_l^1 obtained under the two conditions of H_0 and H_1 ,and Adaboast is used to realize the perception of the master user signal.

Based on PCA and AdaBoost, the spectrum sensing algorithm of main user signal is used to detect the samples. The algorithm is implemented as follows:

Step 1 for the received signal, the cyclic spectrum characteristic parameters are extracted to form the original sample set.

Step 2 the use of PCA for data dimension reduction, after acquisition of Q_1 a primary user exists feature vector as the training sample, among them, any one feature vector to $Y_l^1 = [y_{l1}^1, y_{l2}^1, \cdots, y_{lK}^1]^T$; Acquisition Q_0 characteristic vector of the main user does not exist as the training of the negative samples, among them, a feature vector for $Y_l^0 = [y_{l1}^0, y_{l2}^0, \cdots, y_{lK}^0]^T$.

Step 3 According to section 3.2 AdaBoost algorithm procedures, can be obtained by multiple weak classifier composed of strong classifier $H(x)$.

Step 4 will be collected inQ_1 a positive samples and Q_0 a negative sample training set$G$, and use the training set of G samples for training AdaBoost.

Step 5 repeat step 1and step 2, the positive and negative samples as the sample under test, using AdaBoost training completed for the classification of the primary user signal perception.

4 SIMULATION AND ANALYSIS

In order to validate this algorithm in cognitive network under the condition of low signal-to-noise ratio of primary user signal perception effect, respectively with AM and OFDM signals as the primary user, use Matlab7.0 simulation experiment.AM signal simulation parameters are set as follows: carrier frequency fc=4kHz,sampling points N=1024,sampling frequency fs=500Hz,The frequency range of the sample signal 51Hz to 100Hz.OFDM signal simulation parameters are set as follows: sampling rate fs=4096Hz,symbol rate fb=256Hz,carrier frequency fc=1024Hz,frequency interval is 256Hz,two signals adopts single-stage AdaBoost classification structure, which constitute a strong AdaBoost classifier weak classifier number is 100,the *threshold* value is 0.95.Channel noise is Additive White Gaussian noise. Simulation experiment statistical number is 104 orders of magnitude.

4.1 The performance comparison of the signal detection rates

According to the above parameters, in the case of the average number of training samples for a single experiment is 2000, the number of test samples is 200, using this algorithm for the OFDM and AM signal sample parameters calculation, the generated samples are inserted into the trained AdaBoost strong classifier to obtain the detection rate, and compared with Ann and MME algorithm, the results are shown in Figure 1 and Figure 2.

Figure 1 shows in the OFDM signal, the detection rate of this algorithm and Ann, MME algorithm is compared and analyzed. When the SNR is -15 dB, the detection rate of this algorithm is 0.651, that of Ann is 0.491, and that of MME is 0.135.The detection rate of this algorithm is 16% and 51.6% higher than that of Ann and Mme respectively. When SNR is -5 dB, the detection rate of this algorithm is 0.967, that of Ann algorithm is 0.832, and that of MME algorithm is 0.912, the detection rate of MME is improved by 13.5% and 5.5% respectively. Figure 3 shows the detection rate of the proposed algorithm compared with the ANN and MME algorithms for AM signal. The simulation results show that with the increase of SNR, the detection performance of each algorithm has been improved, but the recognition rate of this algorithm is still significantly higher than that of the other three algorithms. This is because this algorithm uses cyclostationary feature-based principal component analysis and ADABOOST algorithm, its advantage lies in the feature extraction of cyclostationary feature combined with PCA dimension reduction, in addition, AdaBoost is a strong

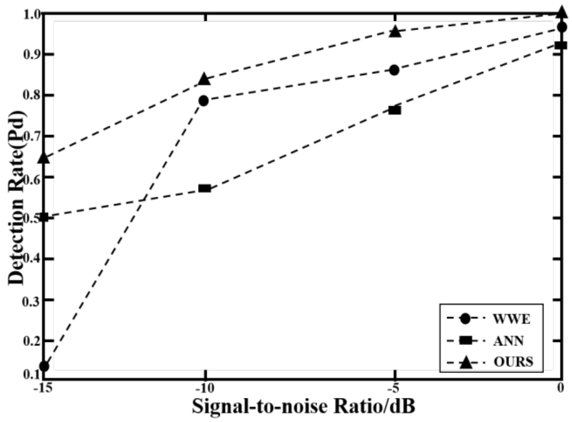

Figure 1: The detection rate of OFDM signal for various algorithms

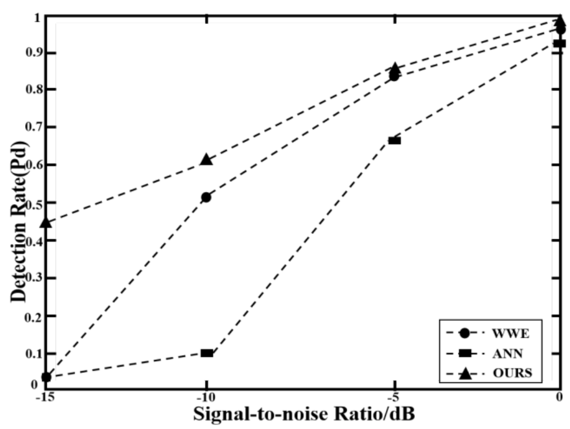

Figure 2: The detection rate of AM signal for various algorithms

classifier composed of several weak classifiers, which shows the advantages of its precise classification detection. At the same time, the algorithm also effectively overcomes the disadvantages of traditional Ann which cannot get the optimal solution due to local optimization and energy detection algorithm under low SNR.

4.2 The performance comparison of the signal false alarm rate

In the case of different noise power, the false alarm rate of the two signals were simulated, the simulation results are shown in Figure 3, figure 4.

As shown in Figure 4, the false alarm rate of this algorithm is compared with that of ANN and MME algorithms under OFDM and AM signals. The false alarm rate of MME algorithm for different noise power is 10-3 order of magnitude, while that of ANN algorithm and this algorithm is 10-4 order of magnitude. The false alarm rate of this algorithm is significantly lower than that of the two comparison algorithms, which further proves the effectiveness of the algorithm.

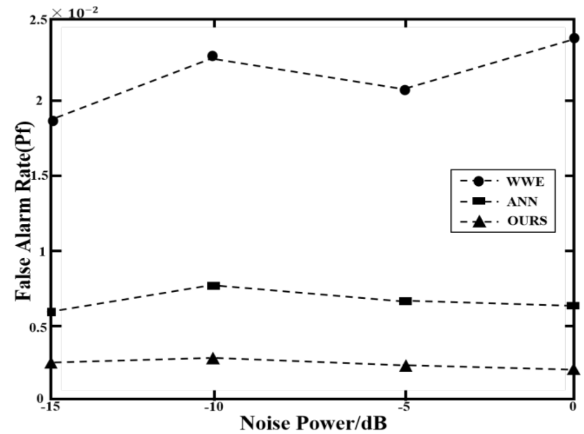

Figure 3: The false alarm rate of OFDM signal for various algorithms

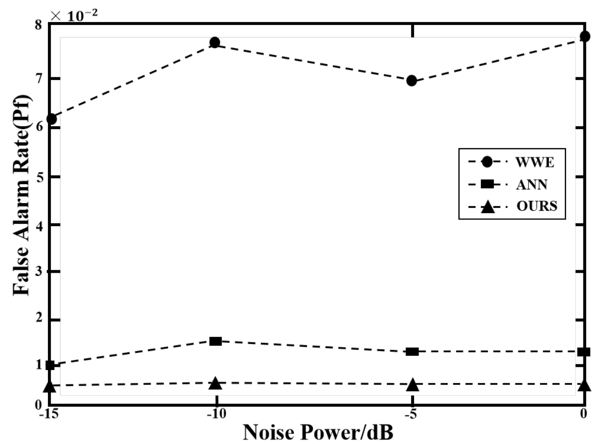

Figure 4: The false alarm rate of AM signal for various algorithms

5 CONCLUSION

In this paper, a new algorithm based on cyclostationary PCA and AdaBoost is proposed, and the main user signal detection problem under low SNR is studied in detail. The simulation shows that the algorithm has good detection performance under low SNR. The algorithm combines cyclostationary feature parameter feature extraction with PCA dimensionality reduction to obtain more accurate sample parameters under the premise of reducing sample dimensions. AdaBoost is a strong classifier composed of multiple weak classifications, highlighting the advantages of its strong classifier for accurate classification and detection. This algorithm effectively overcomes the disadvantages of ANN which cannot obtain the optimal solution due to local optimization and energy detection algorithm in the case of low SNR, and has high recognition accuracy and good robustness.

ACKNOWLEDGMENTS

This work was supported by the Shenyang Science and Technology Plan Project under contact 22-322-3-36.

REFERENCES

[1] Sun H, A Nallanathan, Wang C X, *et al.* Wideband spectrum sensing for cognitive radio networks: a survey. IEEE Journal of Wireless Communications.2013,20(2):74-81.

[2] Sun S, Kadoch M, Gong L, *et al.*. Integrating network function virtualization with SDR and SDN for 4G/5G networks. IEEE Network, 2015,29(3):54-59.

[3] Pourgharehkhan Z,Taherpour A,Sala-Alvarez J,et al. Correlated Multiple Antennas Spectrum Sensing Under Calibration Uncertainty. IEEE Transactions on Wireless Communications,2015,14(12):6777-6791.

[4] Haobo Qing,Yuanan Liu,Gang Xie,Kaiming Liu,andFang Liu. Robust Multiband Spectrum Sensing in Cognitive Radio Networks via Exponentially Embedded Family Criterion, Journal of Communications,vol.9, no.4,pp.357-363,2014.Doi:10.12720/jcm.9.4.357-363.

[5] Yang Liu,Zhangdui Zhong,Gongpu Wang,and Dan Hu. Cyclostationary Detection Based Spectrum Sensing for Cognitive Radio Networks, Journal of Communications, vol.10,no.1,pp.74-79,2015.Doi:10.12720/jcm.10.1.74-79.

[6] Khaled M. Gharaibeh. The Combined Effect of Various Receiver Nonlinearities on Spectrum Sensing in Cognitive Radio Systems, Journal of Communications, vol.15, no.4, pp. 350-358, April 2020.Doi:10.12720/jcm.15.4.350-358.

[7] Wasan Kadhim Saad, Mahamod Ismail, Rosdiadee Nordin, and Ayman A. El-Saleh. Spectrum Sensing Schemes for Dynamic Primary User Signal Under AWGN and Rayleigh Fading Channels, Journal of Communications,vol.11,no. 3,pp.231-242,2016.Doi:10.12720/jcm.11.3.231-242.

[8] Srinivas Samala,Subhashree Mishra,and Subhansu Sekar Singh. Spectrum Sensing Techniques in Cognitive Radio Technology: A Review Paper, Journal of Communications vol. 15, no. 7, pp. 577-582, July 2020. Doi: 10.12720/jcm.15.7.577-582.

[9] Srinivas Samala, Subhashree Mishra,and Sudhansu Sekhar Singh. Cooperative Spectrum Sensing in Cognitive Radio Networks via an Adaptive Gaussian Mixture Model Based on Machine Learning, Journal of Communications vol.17,no.10,pp.812-819,October 2022.Doi:10.12720/jcm.17.10.812-819.

[10] Adamant Sula and Chi Zhou. A Cooperative Scheme for Spectrum Sensing in Cognitive Radio Systems, Journal of Communications,vol.4,no.10,pp.741-751,2009.Doi:10.4304/jcm.4.10.741-751.

[11] Xiaolong Li, Yunqing Liu, Shuang Zhao, and Wei Chu. A Modified Regularized Adaptive Matching Pursuit Algorithm for Linear Frequency Modulated Signal Detection Based on Compressive Sensing, Journal of Communications,vol.11,no.4,pp.402-410,2016.Doi:10.12720/jcm.11.4.402-410.

[12] B. Z. Li, J. H.Shao, and G. N. Wang. An Energy Approximation Model Based on Restricted Isometry Property in Compressive Spectrum Sensing for Cognitive Radio, Journal of Communications,vol.10,no.7,pp.490-496,2015.Doi:10.12720/jcm.10.7.490-496.

[13] M. McHenry.NSF Spectrum Occupancy Measurements Project Summary. tech.rep.Shared Spectrum Co. report, Aug. 2005.

[14] YANG X,LEI K J,PENG S L,et al..Blind detection for primary user based on the sample covariance matrix in cognitive radio. IEEE Communications Letters,2011,15(1):40-42.

[15] ZENG Y H, LIANG Y C. Eigenvalue-based spectrum sensing algorithms for cognitive radio. IEEE Transactions on Communications, 2009, 57(6):1784-1793.

[16] Bkassiny M,Li Y,Jayaweera S.A Survey on Machine-Learning Techniques in Cognitive Radios. IEEE Journal of COMMUNICATIONS SURVEYS & TUTORIALS,2012, 45(5):1-24.

[17] H. Hu, J.Song,and Y.Wang, Signal classifification based on spectral correlation analysis and SVM in cognitive radio. Advanced Information Networking and Applications,2008.AINA 2008.22nd International Conference on,Mar,2008:883–887.

[18] Jolliffe, Principal component analysis. Springer verlag, 2002.

[19] Viola P,Jones M.Rapid object detection using a boosted cascade of simple features. Proceedings of 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Kauai,HI,USA,2001,511-518.