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A Novel Approch On Matching Algorithms

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Abstract*:Prototype-based classifiers are usually clustering-based methods. Therefore, theyrequire a dissimilarity criterion to cluster the drill data and also to assign class labelsto test data. Euclidean distance is a commonly used dissimilarity criterion. However, theEuclidean distance may not be able towards give accurate shape-based comparisons of veryhigh-dimensional signals. This can be problematic for some classification applicationswhere high-dimensional signals are grouped into classes based on shape similarities.Therefore, a reliable shape-based dissimilarity measure is desirable. The Hungarian method proved tobe an effective method for solving assignment problems. Any new primal-dual algorithm must be effective on some class of problems to be of interest. In particular, itmust be associated to the Hungarian method for the assignment problem. With thisin mind, we have tried to determine how the nonnegative least squares primal-dualprocedure relates to the Hungarian method for the assignment problem. We haveestablished several connections between the two algorithms, and more generally, between the nonnegative least squares algorithm and the weighted matching problemon general graphs. In [*6*], the authors showed that the nonnegative least squaresalgorithm is a steepest ascent method for solving the dual of a linear programmingproblem. This means that this method should require fewer ladders, on average, thanthe Hungarian method.* Results were shown effectively in MATLAB
Keywords*:Algoithm, Least Squares, MATLAB, NNLS*

I. Introduction

Object detection and recognition are two important problems in the signal processingdomain. For this purpose, a transmitterreceiver approach is usually employed. Signalsare transmitted in the direction of the suspected target location and the alteration ofthese transmitted waves by the target is received and recorded. For example, radars usereflection of electromagnetic waves to detect aircrafts in air, reflected sound waves are usedto detect vessels under water and the electromagnetic induction (EMI) sensors measurethe secondary electromagnetic field induced in a buried object to detect landmines.The received signals are usually very high-dimensional time or frequency domainsignals. They are analyzed using signal processing and machine learning algorithms forexistence and identi¯cation of the target objects. The object detection task can simplybe to determine if an object exists in the test data, as for the radars used by air tra±ccontrollers to determine the location of aircraft, or it can be more complicated, forexample, by including the recognition of the target. Landmine detection systems thatuse EMI sensors not only need to determine whether an object is buried in the ground,but they also need to recognize whether the buried object is a mine or a non-mine. TheEMI response of a buried object depends on its metallic composition and geometry andstays consistent across most weather and soil conditions. Therefore, the high-dimensional

EMI response contains shape-based information about the target. This information can becharacterized to identify the object as a mine or a non-mine.One approach to classi¯cation is to extracts features that capture the shape anddistinguishing characteristics of signals in the training dataset. These features are thenused to train a discrimination-based classi¯er which learns a decision rule for assigningclass labels to the test data. A discrimination-based classi¯er learns the decision ruleby drawing a decision boundary between training data of both classes in the feature.

II. Methodology

The potential usefulness of the MPDM for a variety of problems is demonstrated bydevising two important MPDM-based algorithms. The first algorithm, called CAMP, dealswith the prototype-based classi¯cation of high-dimensional signals. The second algorithmis called the EK-SVD algorithm and it automates the dictionary learning process for theMP approximation of signals.In the CAMP algorithm, MPDM is used with the Competitive Agglomeration (CA)clustering algorithm by Frigui and Krishnapuram to propose a probabilistic classi¯cationmodel [2]. The CA algorithm is a fuzzy clustering algorithm that learns the optimal number of clusters during training. Therefore, it eliminates the need for manually specifyingthe number of clusters beforehand. This algorithm has been named as CAMP as an abbreviation of CA and MP algorithms. For a two class problem (y 2 f0; 1g), CAMP clustersmembers of each class separately and uses the cluster representatives as prototypes. Theprior probability p(yjcj) of a class is computed based on similarity of the cluster cjtoclusters of the other class. The likelihood p(xjcj) of a point x is determined using MPDM.The likelihood p(xjcj) and the prior p(yjcj) is used to compute the posterior probabilityp(yjx) of x of belonging to a class y. The test point t that has low posterior probabilitiesfor both classes may be considered to be an outlier.Matching pursuits has previously been used as a feature extractor for discriminationbasedclassi¯ers (section 2.3). However, the new CAMP algorithm is the ¯rst methodsthat builds a bridge between clustering and matching pursuits techniques. Therefore,it can be used to combine existing MP-based image compression techniques with theprototype-based image recognition and retrieval applications in one framework. The experimental results also show the usefulness of CAMP for classi¯cation of high-dimensionaldata. The CAMP algorithm has been used for classi¯cation of real landmines detectiondata collected using an electromagnetic induction sensor, discussed. Theclassiffication performance of the CAMP algorithm has been found to be better than anexisting multi-layer perceptron based system for this data. Our CAMP algorithm alsooutperformed support vector machines using non-linear radial basis function as kernel.The experimental results also demonstrate the superiority of MPDM over the Euclideandistance for shape-based comparisons in high dimension. An extensive experiment usingsimulated data is also reported to demonstrate the outlier detection capabilities of CAMPover discrimination-based classi¯ers and the prototype-based classi¯er using the Euclideandistance.

III. Review

Matching pursuits (MP) is a well known technique for sparse signal representation.MP is a greedy algorithm that ¯nds linear approximations of signals by iteratively projecting them over a redundant, possibly non-orthogonal set of signals called dictionary. SinceMP is a greedy algorithm, it may give a suboptimal approximation. However, it is usefulfor approximations when it is hard to come up with optimal orthogonal approximations,as in the case of high-dimensional signals or images. Historically, matching pursuits (MP)technique is used for signal compression, particularly audio, video and image signal compression. However, MP has also been used in some classi¯cation applications, usually as afeature extractor.This chapter is an overview of the Matching Pursuits algorithm, its dictionaries andits application to the classi¯cationproblems. Therefore, we discuss indetail the de¯nition and characteristics of the MP algorithm and also some commonlyused improvements over the basic MP algorithm. The dictionary plays a pivotal role inperformance of the MP algorithm, therefore we discuss in detail some wellknown MP dictionaries and also the dictionary learning methods. Since we are trying toadopt the MP algorithm for classiffication purposes, in Section 2.3 we review the existingdiscrimination and model based classi¯cation systems that use the MP algorithm.

IV. Algorithm

Matching Pursuits (MP) is an algorithm that expresses any signal x as a linearcombination of elements from a set of signals called the dictionary [1]. It was reintroducedfrom the statistical community to the signal processing community by Mallat and Zhangin 1993 [8]. Let H be a Hilbert space, then matching pursuits decomposes a signalx 2 H through an iterative, greedy process over an overcomplete set of signals, calledthe dictionary D = fg.

At each iteration the dictionary element that is the most similar to the residueis chosen and subtracted from the current residue. If the angle of projection at eachiteration is small, then it will take only a few iterations to drive the residue to zero.Conversely, if at each iteration the angle of projection between the residue and the chosenelement is large, it will take more iterations and dictionary elements to reduce the residuesignificantly. In addition, if the dictionary is large, then the computation time of theiterations will be large. Hence the proper choice of dictionary is essential. Since MPis a greedy algorithm, the chosen coefficients should get smaller as the iteration index,j , gets larger. Hence, the maximum information about the signal x is contained in the first few cofficients. Therefore, MP also has a denoising effect on the signal x. Sparsityof representation is an important issue, both for the computational efficiency of theresulting representations and for its theoretical and practical influence on generalizationperformance. The MP algorithm provides an explicit control over the sparsity of theapproximation solution through choice of a suitable value of p.

Theorem 1. *Algorithm 1 terminates with a solution of problem* (*PLS*).

1. Let B be the feasible basis for problem P
2. Let I_B be the index set of the columns in B
3. $\bar{x} \leftarrow B^{+}b$
4. $\pi \leftarrow b - B\bar{x}$
5. $S \leftarrow \{j : A_j > 0\}$
6. if $S = \phi$ the

7. stop: optimal solution found
8. end if
9. Let $k \in s$
10. $d \leftarrow B^{+} A_{k}$
11. $\theta \leftarrow \min_{d_j > 0 \frac{x_j}{d_j}}$
12. $P \leftarrow I - BB^{+}$
13. $\theta \leftarrow \dfrac{\pi^{t} A_{j}}{\left\| PA_{j} \right\|^{2}}$
14. $\theta \leftarrow \min\left\{ \theta, \bar{\theta} \right\}$
15. if $\theta = \bar{\theta}$ then
16. $I_{B} \leftarrow I_{B} \cup \{j\}$
17. if $\theta = \bar{\theta}$ then
18. $\bar{x}(\theta) \leftarrow \bar{x}_{j} - \theta d_{j}$
19. $I_{B} \leftarrow I_{B} - \{j : x(\theta) = 0\}$
20. end if
21. $B \leftarrow \lfloor A_{j} \rfloor, \forall_{j} \in I_{B}$
22. Return to 3
23. else
24. $I_{B} \leftarrow I_{B} \left\{ J : \theta = \dfrac{\bar{x}_{j}}{d_{j}} \right\}$
25. $B \leftarrow \lfloor A_{j} \rfloor, \forall_{j} \in I_{B}$
26. $\bar{x} \leftarrow B^{+} b$
27. Return to 10
28. end if

V. Outputs

This estimation is itself then sampled, and the residual of thesignal is updated. Let x ∈ Rd and let u = Φx be the measurement vector.The HHS Pursuit algorithm produces a signal approximation xˆ with O(s/ε2) nonzeroentries. k x − xˆ k 2 ≤ √εs k x − xsk 1,where again xs denotes the vector consisting of the s largest entries in magnitudeof x. The number of measurements m is proportional to (s/ε2) polylog(d/ε), andHHS Pursuit runs in time (s2/ε4)polylog(d/ε). The algorithm uses working space(s/ε2)polylog(d/ε), including storage of the matrix Φ.

There are other algorithms such as the Sudocodes algorithm that as of now onlywork in the noiseless, strictly sparse case. However, these are still interesting becauseof the simplicity of the algorithm. The Sudocodes algorithm is a simple two-phasealgorithm. In the first phase, an easily implemented avalanche bit testing schemes applied iteratively to recover most of the coordinates of the signal x. At thispoint, it remains to reconstruct an extremely low dimensional signal (one whosecoordinates are only those that remain). In the second phase, this part of the signalis reconstructed, which completes the reconstruction. Since the recovery is twophase, the measurement matrix is as well. For the first phase, it must contain asparse submatrix, one consisting of many zeros and few ones in each row. For thesecond phase, it also contains a matrix whose small submatrices are invertible. Thefollowing result for strictly sparse signals.Combinatorial algorithms such as HHS pursuit provide sublinear timerecovery withoptimal error bounds and optimal number of measurements. Some of these arestraightforward and easy to implement, and others require complicated structures.The majordisadvantage however is the structural requirement on the measurementmatrices. Not only do these methods only work with one particular kind of measurement matrix, but that matrix is highly structured which limits its use in practice.There are no known sublinear methods in compressed sensing that allow for unstructured or generic measurement matrices

OUTPUTS

Fig 1 Computation time for the fixed N = 256 and K = 24 & 32

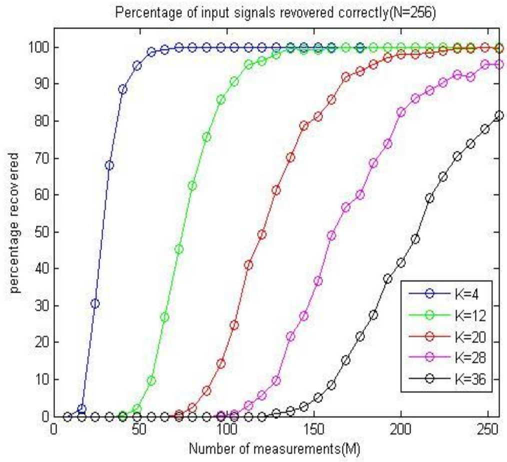


Fig 2: Average exact recovery and Computational time(sec

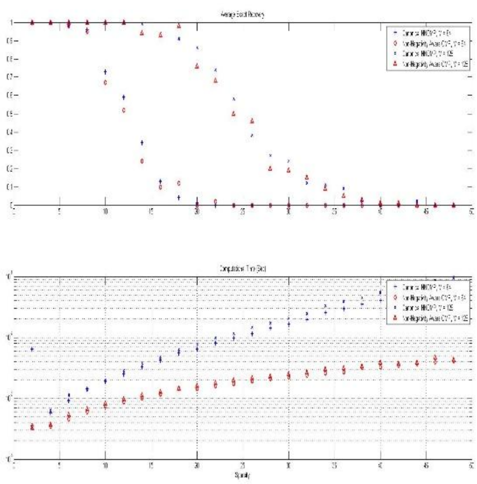
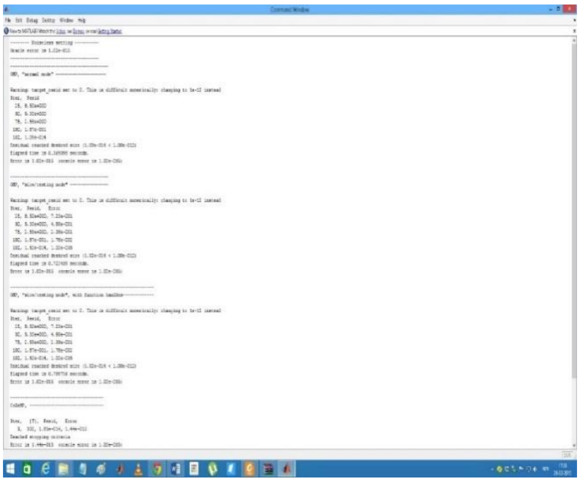


Fig. 3. Computation time for the fixed M = 128 and K = 64 & 96

Fig 4: Percentage of recovered signals



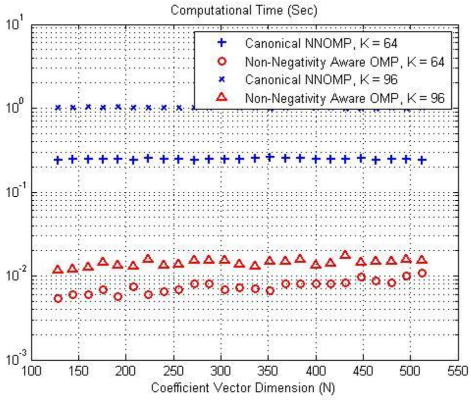


Fig 5: Sparse AOMP data

VI. Conclusion

A matching pursuits dissimilarity measure has been presented, which is capableof performing accurate shape-based comparisons between high-dimensional data. Itextends the matching pursuits signal approximation technique and uses its dictionaryand coefficient information to compare two signals. MPDM is capable of performingshape-based comparisons of very high dimensional data and it can also be adapted toperform magnitude-based comparisons, similar to the Euclidean distance. Since MPDMis a differentiable measure, it can be seamlessly integrated with existing clusteringor discrimination algorithms. Therefore, MPDM may find application in a variety ofclassiffication and approximation problems of very high dimensional data.The MPDM is used to develop an automated dictionary learning algorithm for MPapproximation of signals, called Enhanced K-SVD. The EK-SVD algorithm uses theMPDM and the CA clustering algorithm to learn the required number of dictionaryelements during training. Under-utilized and replicated dictionary elements are graduallypruned to produce a compact dictionary, without compromising its approximationcapabilities. The experimental results show that the size of the dictionary learned by ourmethod is 60% smaller but with same approximation capabilities as the existing dictionarylearning algorithms.The MPDM is also used with the competitive agglomeration fuzzy clustering algorithm to build a prototype-based classi¯er called CAMP. The CAMP algorithm buildsrobust shape-based prototypes for each class and assigns a con¯dence to a test patternbased on its dissimilarity to the prototypes of all classes. If a test pattern is di®erent fromall the prototypes, it will be assigned a low con¯dence value. Therefore, our experimentalresults show that the CAMP algorithm is able to identify outliers in the given test databetter than discrimination-based classi¯ers, like, multilayer perceptrons and support vectormachines.

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