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Sparse Face Recognition System Using OMP

Sujitha P.[1], Dr. Arathi T.[2]

Student, M.Tech, VLSI Design & Signal Processing, LBS College of Engineering, Kasaragod, Kerala, India[1]

Assistant Professor, ECE Department, LBS College of Engineering, Kasaragod, Kerala, India[2]

Abstract: It is very challenging to recognize face images with illumination and expression variations in the presence of missed information, hence it turns to be an active research topic. This paper presents a greedy algorithm called Orthogonal Matching Pursuit (OMP) which can be proved theoretically and empirically that a signal with many zero entries can be recovered reliably**.** Existing sparse algorithms are basis pursuit, matching pursuit (MP) and Lasso. OMP differs from MP, in that the columns in MP are not orthonormal where as in OMP the column vectors are made orthonormal before start . The running time of MP is high when compared to OMP. The idea of sparse is widely used for implementing all these algorithms. The term sparse refers to a measurable property that concerns the number of non-zero entries present in a vector termed as sparsity. Recognition of a sparse image is presented here. OMP is an iterative algorithm which takes the images as the columns of a dictionary. The algorithm selects the column vector which most closely resembles a residual vector.A global optimum solution is obtained from sequence of locally optimum solutions.

Keywords: sparse, sparsity, orthogonal matching pursuit, basis pursuit, matching pursuit.

I. INTRODUCTION

From the recent diversity of face recognition it can be seen that studies on face recognition are being actively conducted. Recently there has been a growing interest in sparse approximations. This is due to their vast amount of applications. There is no general method guaranteed to work in every situation so that the task of finding sparse approximations can be very difficult. Finding a sparse approximation is just an abstract mathematical problem. Sparse approximations have a wide range of practical applications. Vectors are often used to represent large amounts of data which can be difficult to store or transmit. By using a sparse approximation the amount of space needed to store the vector would be reduced to a fraction of what was originally needed. The applications will include signal recovery, approximation, denoising purposes, compressive sensing, feature extraction, inpainting etc.

Traditional face recognition methods can be classified into three types. First, appearance-based face recognition methods use global feature extracted from the face region. Principal components analysis (PCA) and linear discriminant analysis (LDA) can be categorized as appearance-based methods. Second, texture-based face recognition methods use textural characteristics extracted from the local face region. In texture-based methods, local binary pattern (LBP) is generally used. Third, geometry-based face recognition uses the positions of feature points such as the eyes, nose, and mouth. For example, the active appearance model is regarded as a geometry-based method[18].

If the input image for the face recognition system is having some distortion or any other disturbances itself it will result some sort of reduction in its efficiency. Traditional face recognition systems will face such a scenario. This paper gives the remedy for such problems through the idea of sparse. Even if the input image had lost
some of its data and this lost data is considered as zero then by treating such an image as a sparse image, by applying appropriate sparse algorithms an efficient face recognition system can be implemented. Compared with other alternative methods such as basis pursuit, matching pursuit, Lasso etc. a major advantage of the OMP is its simplicity and fast implementation. The OMP is a stepwise forward selection algorithm and is easy to implement. A key component of OMP is the stopping rule which depends on the scenario where the application takes place. Stopping criteria for OMP is another parameter which will differ under various applications and also depends on the characteristics of images on which the operations should take place. The stopping condition for noiseless image will depend on the value of residual and in the case of noisy images type of noise will decide the criteria.

This paper illustrates the idea of sparse face recognition system using the basic sparse algorithm called Orthogonal Matching Pursuit (OMP) algorithm. It is an iterative algorithm that select each column which is most correlated with an already defined value called a residual. The proposed method gives the simplified approach for face recognition by using OMP. The experiment is performed on few standard image data.

This paper is organized as seven sections. section two includes existing sparse algorithms, third section gives the idea of sparse processing, Orthogonal Matching Pursuit algorithm will be discussed in fourth section, fifth section explains how a face recognition can be implemented by using this OMP algorithm, experimental results and analysis are given in sixth section finally this paper will be concluded.

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II. SPARSE ALGORITHMS

The methods used to solve sparse approximation problems are available in a variety of way. The two most common methods in use are the lasso and orthogonal matching pursuit.

Philip Breen[6] reveals a method known as basis pursuit which is related to the Lasso algorithm. The idea of Basis Pursuit is to replace the difficult sparse problem with an easier optimization problem. Below the formal definition of the sparse problem is given:

Sparse problem: min $||x||_0$ subject to **Ax = b**

Where $||x||_0$ is the L0 norm. Basis Pursuit replaces the L0 norm with the L1 to make the problem easier.

Basis Pursuit: min $||x||_1$ subject to **Ax = b**

Above problem can be found a solution with relative ease. There are methods that will find the solution to the BP problem but does it lead to a sparse solution. Under the correct conditions it can be guaranteed that b will find a sparse solution. This happens because L1 norm is only concerned with the value of entries not on the quantity. A vector with a small L1 could have very small valued non zero entries in every position which would give it a large L0 norm.

Robert Tibshirani[16] gives the idea about Lasso algorithm which is similar to that of basis pursuit. It is known as Basis Pursuit De-Noising (BPDN) in some areas. The Lasso trying to minimize the L1 norm like BP places a restriction on its value.

The Lasso: min **||Ax-b||2** subject to $||x||1 < \lambda$

The Lasso allow us to find approximations other than just representations and like BP can be guaranteed to find the sparsest solution under the right conditions.

Thong T. Do et al[17]. describes the idea of matching pursuit algorithm. Matching pursuit is a greedy algorithm that computes the best nonlinear approximation to a signal in a complete, redundant dictionary. Matching pursuit builds a sequence of sparse approximations to the signal stepwise. Let $\Phi = \{\varphi k\}$ denote a dictionary of unit-norm atoms. Let *f* be your signal.

Steps in algorithm are;

1. Start by defining $R^0 f = f$
2. Begin the matching pursuit by selecting the atom from the dictionary that maximizes the absolute value of the inner product with $R^0 f = f$. Denote that atom by φ_p.
3. Form the residual $R^1 f$ by subtracting the orthogonal projection of $R^0 f$ onto the space spanned by φ_p.

$$R^1 f = R^0 f - \langle R^0 f, \phi_p \rangle \phi_p$$

4. Iterate by repeating steps 2 and 3 on the residual.

$$R^{m+1} f = R^m f - \langle R^m f, \phi_k \rangle \phi_k$$

5. Stop the algorithm when you reach some specified stopping criterion

III. SPARSE PROCESSING

Sparse processing is a typical area in both the signal and image processing. Sparse approximation case is considered here. Before going to what sparse approximation is there should be an idea about what is sparse. A sparse in its simplest definition is a signal or image which will be having many no. of zeros in its nature. Sparsity is the term which measures the count of no. of non-zeros present.Usually L0 norm is used asthe method to measure the sparsity of a vector. Informally the L0 norm is simply the number of non-zero entries in a vector. A lot of advantages are there working with sparse vectors. It requires less space when being stored on a computer since the position and value of the entries need to be recorded. There are many different methods used to solve sparse approximation problems namely Lasso, basis pursuit, matching pursuit. The lasso a convex problem. One of the motivations for change to a convex problems is there are algorithms which can effectively find solutions. Orthogonal matching pursuit is a greedy method for solving the sparse approximation problem. This method is very straight forward as the approximation is generated by going through an iteration process. During each iteration the column vectors which most closely resemble the required vectors are chosen. These vectors are then used to build the solution. Sparse processing involves the processing of such sparse signal. Suppose a signal or image got corrupted and lost information are treated as zero value. One can use the idea of sparse and with the help of appropriate sparse processing techniques efficient results can be achieved.

IV. ORTHOGONAL MATCHING PURSUIT ALGORITHM

Orthogonal matching pursuit (OMP) is an iteration processwhich constructs an approximation by going through each iteration. Locally optimum solutions are calculated at each iteration.It finds the column vector in A which most closely resembles a residual vector r. The residual vector starts out being equal to the vector that is required to be approximated as r = b and is adjusted at each iteration to take into account the vector previously chosen. It is the hope that this sequence of locally optimum solutions will lead to the global optimum solution. OMP is based on a variation of an earlier algorithm called Matching Pursuit (MP). Suppose that x is an arbitrary m-sparse signal and let {x1. . . xN} having N measurement vectors.

Form an N × d matrix with columns as the measurement vectors, and observe that the N measurements of the signal can be collected in an N-dimensional data vector. v = Ax. A as the measurement matrix andAj denotes its columns. Since v has only m nonzero components, the data vector v = Ax is a linear combination of m columns from A. In the language of sparse approximation, To identify the ideal signal x, determine which columns of A participate in the measurement vector v. At each iteration, choose the column of A that is most strongly correlated with the remaining part of v. Then we subtract off its contribution to v and iterate on the residual.

Algorithm

Input:

- An N × d dictionarymatrix A
- An data vector v of N dimension
- Thesparsity measurement m of the signal

Output:

- xk– the sparse vector of size N × 1 having m nonzero elements.

Steps in algorithm are:

1. The dictionary matrix A = [A1, A2 ...AN] of size N × d is formed.
2. The residual rn is initialized as *b*, the active index=0, and the iteration counter, k=1.
3. Find the new index which solves the minimization problem

newindex = arg max j=1, 2...N <rn,Aj>

4. Update the augmented matrix Ak

Ak = [Ak−1 Anewindex]

Here Ak is the updated dictionary of dimension $N \times k$ and is an empty matrix. That is, append the corresponding column vector of A to the augmented matrix AK.

5. New sparse vector *xk*is:

arg min ||Akxk-bn||2

Xk

$Xk= (Ak^{T}Ak)^{-1} * Ak^{T} * b$

6.Calculate the new approximation of the data and thenewresidual.

bn = Akxk

rn = b −bn

7. Increment k, and return to step (3) if k <m

The non-zero elements of xk will be at the location corresponding to the respective column number of the dictionary matrix at the end of iteration. A from which that element is obtained and the rest element will be zero, making it a sparse vector xk will now have the size $N \times 1$

V. FACE RECOGNITION USING OMP

Dictionary is the basic element of this algorithm. Here a dictionary is created using the standard images from Extended Yale B database. Different variations of face images are taken and each image is represented as the columns of the dictionary.

Inner products between input image and each columns of dictionary are calculated .Find the column which maximizes the inner product value , then put that image into another matrix .since it is a greedy algorithm it uses an iterative manner with iteration count as the sparsity of input image itself. Sparsity measures the number of nonzero values in the input image.

Initial value of residual is the input image itself. After completing the first iteration value of residual should be updated. In order to update the residual a sparse vector is needed, and q is calculated using the augmented matrix which includes selected column of the dictionary. Apply this sparse vector on the augmented dictionary and subtract it from the first value of residual. Repeat the process of finding inner products and so on until the count of iteration becomes equal to sparsity.

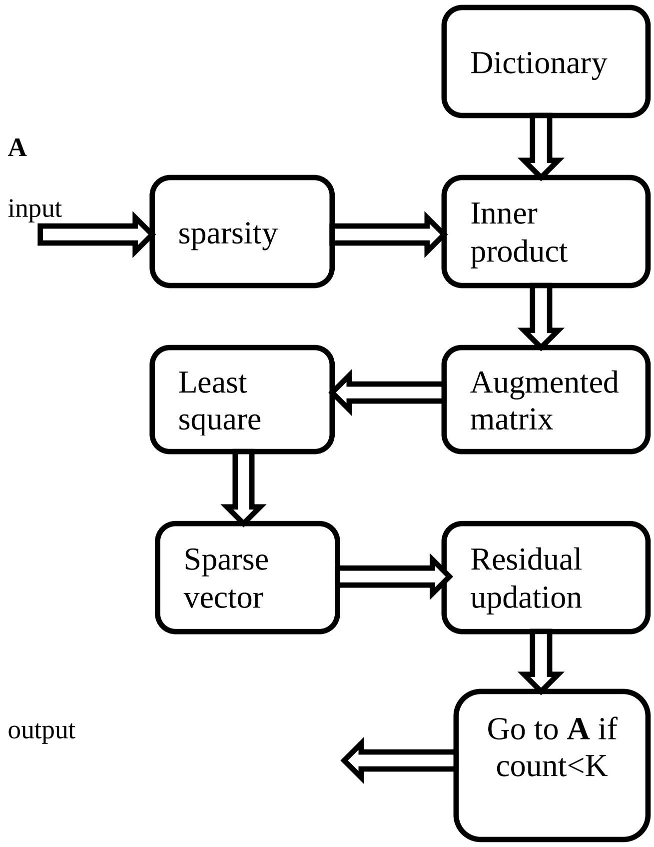


Fig 1.Block diagram for face recognition

Mathematically, least squares is the problem of approximately solving an overdetermined system of linear equations. The best approximation is defined as that which minimizes the sum of squared differences between the data values and their corresponding modeled values[4]. The sum of the squares of the errors made in the results of every single equation is minimized in least square approach. The most important application is in data fitting.

Problem statement

$\arg\min_{Xk} \|\mathbf{Akxk-b}\|_2$:associated with L_2 norm.

$$\|Akxk-b\|_2 = (Akxk-b)^T (Akxk-b)$$

$$J(x) = Ak^T xk^T Akxk - Ak^T xk^T - b^T Akxk + b^T b$$

Taking its derivative and equating to zero will give the solution xk which minimizes the problem.

$$\frac{\partial J(x)}{\partial x} = 0 \;;$$

$$\Rightarrow \quad 2\, Ak^T Akxk - 2Ak^T$$

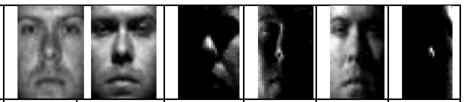
$$Xk = (Ak^T Ak)^{-1} * Ak^T * b$$

Xk is the sparse vector which is used to find out Akxk , and is subtracted from the residual value.

VI. EXPERIMENTAL RESULTS AND ANALYSIS

This paper is implemented with the help of MATLABR2015a version. Various images of three persons are selected from the standard Extended Yale B database and which are taken in tiff format.

Face recognition results

Input images						
Whether recognised or not	Yes	Yes	No	Yes	Yes	No

(a)

Input images						
Whether recognised or not	yes	yes	yes	yes	yes	no

(b)

Input images						
Whether recognised or not	yes	no	yes	yes	yes	no

(c)

Fig: (a)various input images and recognition results for set 1,(b)various input images and recognition results for set 2, various input images and recognition results for set 3

Traditional face recognition requires input images which are not having any disturbances in its nature. Where as sparse based face recognition will give a better result even if the input image had lost many of its information. The sensitivity of sparse based face recognition system results high when compared to traditional methods.

VII. CONCLUSION

As a part of face recognition, implemented a basic sparse algorithm called orthogonal matching pursuit algorithm, which uses the minimum mean square error criteria and searches each of the column vector of the basic gallery and choose the output as the one with minimum mean square error. This paper is experimented on few standard image data set. Sparse algorithms can have many applications including compressive sensing, denoising etc. The face recognition strategy is successfully implemented by using the images from the standard data base namely Extended Yale B database

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