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Over-Atoms Accumulation Orthogonal Matching Pursuit Reconstruction Algorithm for Fish Recognition and Identification

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***Abstract*—Fish recognition and identification in an underwater environment are important research topics. In this study, several real-world underwater videos were collected to construct a fish category database for further fish recognition and identification. Recently, compressive sensing, using reconstruction algorithms to reconstruct a sparse signal, has been successfully applied to face recognition. Reconstruction algorithms can be roughly categorized into two groups: basic pursuit (BP) and matching pursuit (MP). BP-related methods adopt a convex optimization technique, while MP-related methods utilize greedy search and vector projection ideas. This study reviews concepts for these reconstruction algorithms and analyzes their performance. Moreover, an over-atoms accumulation orthogonal matching pursuit (OAOMP) method based on OMP is proposed. OAOMP includes two procedures: picking over atoms, and accumulating weighting coefficients of each subject to assign as new weights. OAOMP was compared with existing reconstruction algorithms in terms of reconstruction performance and run time. Experiments were implemented in a fish category database by using eigenfaces and fisherfaces for feature extraction. The experimental results demonstrated that BP-related methods have better recognition rates, while MP-related methods have shorter run times. Moreover, OAOMP is able to achieve better accuracy than OMP and other MP-related methods.**

Keywords—compressive sensing; orthogonal matching pursuit; pattern recognition

I. Introduction

Taiwan has a rich set of marine resources, including a variety of coral reefs and diversity of fish species. Underwater fish observation is important to help ecologists study the populations and habits of fish in particular areas of interest. A distributed underwater real-time stream system has been developed and operated for long term observation at the southern tropical coast of Taiwan [1]. Based on the stream system, 25 different and popular species of fish were collected to construct a fish category database for further fish recognition and identification. The 25 species of fish selected from the fish category database are shown in Fig. 1.

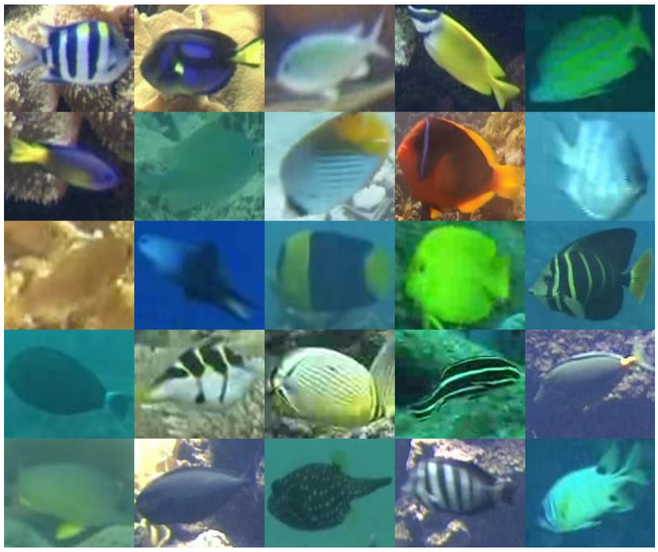

Fig. 1. The 25 species of fish selected from the fish category database.

Recently, compressive sensing (CS) [2, 3], a sampling method based on the sparsity principle, was proposed to reconstruct signals exactly from far fewer samples of measurements beyond Nyquist rates [4]. Two kinds of widely studied reconstruction algorithms in CS are basis pursuit (BP) [5] and matching pursuit (MP) [6]. The performance of reconstruction by BP is superior to MP, however, BP requires much more computing time than MP. In order to improve the performance of MP, several modified versions of MP, such as orthogonal matching pursuit (OMP) [7], compressive sampling matching pursuit (CoSaMP) [8], subspace pursuit (SP) [9], and regularized OMP (ROMP) [10] have been proposed. OMP utilizes orthogonal projection to improve efficiency. CoSaMP and SP iteratively update the atoms to eliminate incorrectly selected atoms by using a backtracking technique. ROMP reduces computational cost by selecting multiple atoms at each iteration.

CS has been widely implemented in numerous applications, including pattern recognition, computer vision, and image processing. A sparse representation-based classification (SRC) method [11] based on CS was proposed and successfully applied in face recognition. This study proposed an over-atoms accumulation OMP (OAOMP) method based on SRC and OMP for fish recognition and identification. Experiments were implemented in our constructed fish category database and a popular face database, Extended Yale B; meanwhile, eigenfaces [12] and fisherfaces [13] were used for feature extraction. The proposed method enabled higher recognition rates than MP-related methods.

The rest of this paper is organized as follows: Section 2 briefly reviews several existing CS reconstruction algorithms. Section 3 presents the proposed method for fish recognition and identification. Section 4 depicts experiment results and conclusions are drawn in Section 5.

II. Review of Compressive Sensing Reconstruction Algorithms

In CS, a K-sparse signal $\mathbf{x}_0 \in \mathbb{R}^N$ means the signal owns at most K nonzero coefficients where $K \ll N$. Reconstruction algorithms are used to process a K-sparse signal and find sparse solutions. They reconstruct $\mathbf{x}_0$ from an underdetermined system $\mathbf{y} = \Psi\mathbf{x}_0$, where $\Psi \in \mathbb{R}^{M\times N}$ is a measurement matrix, and $\mathbf{y} \in \mathbb{R}^M$ is a measurement vector ($M \ll N$).

A. Basis Pursuit

The most popular reconstruction algorithm in CS is basis pursuit (BP) which can reconstruct a sparse signal with high accuracy by solving a convex optimization problem through linear programming (LP) [14]. The l_1 norm minimization

$$\min\|\mathbf{x}\|_1 \text{ subject to } \Psi\mathbf{x} = \mathbf{y} \tag{1}$$

has been done to show that it is an efficient method for solving LP [15, 16]. The solution of l_1 norm minimization is unique and equal to $\mathbf{x}_0$. Several BP-related methods have been proposed, such as the primal-dual method (PD) [17] and a general-purpose convex programming toolbox CVX [18] which is easily and widely used, including the minimum residual method (SRC-RES) [11] and maximum probability of partial ranking method (SRC-MP) [19] based on SRC. The advantages of BP-related methods are high performance and robustness, while weakness includes their high computation complexity.

B. Matching Pursuit

Matching pursuit (MP) [6] is an iterative greedy algorithm which takes advantages of greedy search and vector projection to reconstruct a sparse signal. It reconstructs the K-sparse signal by iteratively constructing a support set S of the signal. At each iteration, MP optimizes the approximation by selecting one column (called an atom) which has the maximum correlation (the inner product with largest absolute value) with the residual $\mathbf{r}$ from the measurement matrix Ψ (called dictionary D). Then, MP updates the support set by appending the selected atoms till the termination criterion occurs. The drawbacks of MP are its slow convergence and poor sparse reconstruction performance.

C. Orthogonal Matching Pursuit

OMP [7], an improved version of MP, has the capability to eliminate MP drawbacks by projecting the signal orthogonally onto the set composed of all selected atoms. The principle of OMP is the same as MP, but a major difference is that OMP never chooses an atom that was selected in previous iterations since the residual $\mathbf{r}$ is orthogonal to the already chosen atoms.

The main steps of OMP are as follows:

Initialization: The residual $\mathbf{r}_0 = \mathbf{y}$, the support set $\mathrm{S}_0 = \emptyset$.

Repeat the following steps K times.

1) Identify: Find the index λ_t of the atom ψ_i with the largest absolute value of inner product.

$$\lambda_t = \arg\max_{1\le i\le N}|\langle\mathbf{r}_{t-1}, \psi_i\rangle| \tag{2}$$

2) Merge: Merge the current selected atom with the previous support set S_{t-1}.

$$\mathrm{S}_t = \mathrm{S}_{t-1} \cup \lambda_t,\ \Psi_t = [\Psi_{t-1}\psi_{\lambda_t}] \tag{3}$$

3) Estimation: Compute the sparse coefficient by using least squares.

$$\mathbf{x}_t = \arg\min_{\hat{\mathbf{x}}}\|\mathbf{y} - \Psi_t\hat{\mathbf{x}}\|_2 \tag{4}$$

4) Update: Estimate new approximation $\mathbf{a}_t$ and update the residual.

$$\mathbf{a}_t = \Psi_t\mathbf{x}_t,\ \mathbf{r}_t = \mathbf{y} - \mathbf{a}_t \tag{5}$$

D. Compressive Sampling Matching Pursuit

CoSaMP [8] incorporates a backtracking technique to refine the previous selected atoms. Moreover, CoSaMP utilizes a multiple atoms selection procedure to accelerate computation speed. At each iteration, it picks up $2K$ largest atoms and merges the selected atoms with the current support set. Then, CoSaMP adds a new pruning step which keeps the K largest atoms and prunes the others in order to keep the size of the support set as K. Thus, CoSaMP is able to eliminate incorrectly selected atoms that OMP cannot.

The main steps of CoSaMP are as follows:

Repeat the following steps until the halting criterion has been satisfied.

1) Identify: Form a signal proxy, and find the largest $2K$ atoms of the proxy.

$$\mathbf{u} = \{u_i | u_i = |\langle\mathbf{r}, \psi_i\rangle|, i = 1,2,\dots,N\} \tag{6}$$

$$\Omega = \mathrm{supp}(\mathbf{u}_{2K}) \tag{7}$$

2) Merge: Merge the support of the signal proxy with the support set of the previous iteration.

$$\mathrm{S}_t = \Omega \cup \mathrm{S}_{t-1} \tag{8}$$

3) Estimation: Estimate the solution by using least squares.

$$\bar{\mathbf{x}} = \arg\min_{\hat{\mathbf{x}}} \|\mathbf{y} - \Psi_i \hat{\mathbf{x}}\|_2 \tag{9}$$

4) Pruning: Produce a new approximation by retaining only the largest K atoms in $\bar{\boldsymbol{x}}$.

$$\mathbf{x}_t = \bar{\mathbf{x}}^{(K)} \tag{10}$$

5) Update: Update the residual.

$$\mathbf{r}_t = \mathbf{y} - \Psi \mathbf{x}_t \tag{11}$$

E. Subspace Pursuit

The procedure of SP [9] is quite similar to CoSaMP, and it can also update the selected set based on the backtracking concept. The main difference between SP and CoSaMP is in the manner in selecting atoms. CoSaMP selects *2K* atoms at each iteration, while SP selects only K atoms. At each iteration, SP utilizes two tests to refine the selected set. The preliminary test is to find the most K correlated atoms and merge to the support set. Then, it refines the function to find the K largest atoms from the merged set. SP not only has low computation complexity compared with OMP, but also has good accuracy reconstruction that is the same as that of BP methods.

F. Regularized Orthogonal Matching Pursuit

ROMP [10] also selects multiple atoms at each iteration. It selects the K (sparsity) atoms with the largest absolute value of the inner product to construct an energy set E. Then, in the regularized step, it only considers the subset E_0, which has maximal energy among all subsets of E.

The main steps of ROMP are as follows:

Repeat the following steps K times or until $|\mathrm{I}| \geq 2K$, where I is an index set.

1) Identify: Find the K largest atoms of the observation vector $\mathbf{u}$, and construct an energy set E.

$$\mathbf{u} = \{u_i | u_i = |\langle \mathbf{r}, \psi_i \rangle|, i = 1,2, \dots, N\}, \tag{12}$$

$$\mathrm{E} = \mathrm{supp}(\mathbf{u}_K) \tag{13}$$

2) Regularize: Among all subsets $\mathrm{E}_0 \subset \mathrm{E}$.

$$|\mathbf{u}(i)| \leq 2|\mathbf{u}(j)| \text{ for all } i, j \in \mathrm{E}_k \tag{14}$$

$$\mathbf{u}_{\mathrm{E}_0} = \arg\max \{\|\mathbf{u}_{\mathrm{E}_k}\|_2, k = 1,2, \dots, K\} \tag{15}$$

3) Estimation: Compute the sparse coefficient by using least squares.

$$\mathbf{x}_t = \arg\min_{\hat{\mathbf{x}}} \|\mathbf{y} - \Psi_t \hat{\mathbf{x}}\|_2 \tag{16}$$

4) Update: Add the set E_0 to the index set and update the residual.

$$\mathrm{I}_t = \mathrm{I}_{t-1} \cup \mathrm{E}_0, \ \mathbf{r}_t = \mathbf{y} - \Psi \mathbf{x}_t \tag{17}$$

The run time of ROMP is significantly shorter compared to OMP, but reconstruction performance is worse than OMP.

III. Our Proposed Method

A. Fish Recognition Method

A sparse representation-based classification (SRC) method [11] based on CS was proposed for robust face recognition. It represents a testing image $\mathbf{y}$ of the i^{th} subject as a sparse linear combination of all training images, i.e. $\mathbf{y} = \Psi \boldsymbol{\alpha}$, where $\Psi = [\psi_1, \psi_2, \dots, \psi_K]$ is the concatenation of the N training images from all of the K subjects, and ψ_i is the set of training images of the i^{th} subject. $\boldsymbol{\alpha} = [\boldsymbol{\alpha}^{(1)}; \boldsymbol{\alpha}^{(2)}; \dots; \boldsymbol{\alpha}^{(K)}]$ is the set of weighting coefficients, where $\boldsymbol{\alpha}^{(i)} = [\alpha_1^{(i)}, \alpha_2^{(i)}, \dots, \alpha_{n_i}^{(i)}]^T$ and n_i is the number of the i^{th} subject. These weighting coefficients can be obtained by using reconstruction algorithms. Due to $\mathbf{y}$ belonging to the i^{th} subject, only the coefficients in $\boldsymbol{\alpha}^{(i)}$ have significant values, and all the coefficients in $\boldsymbol{\alpha}^{(j)}$, $j=1,2,\dots,K$ and $j \neq i$, are nearly zero. In the noiseless case, the correct K atoms will be selected using OMP algorithm. As to the noise case, however, the incorrect atoms may be selected. In order to address a noise case and improve reconstruction performance, an over-atoms accumulation orthogonal matching pursuit (OAOMP) method based on SRC and OMP was proposed in this study for fish recognition and identification. OAOMP includes two procedures: picking over atoms and accumulating the weighting coefficients for each subject to assign as new weights. The first procedure of OAOMP is to set the pre-defined number of iteration K' to be greater than the signal sparsity K that over atoms will be picked. The selected over atoms include more correct atoms, since the atoms founded by setting $K' > K$ will contain the atoms found by setting $K' = K$. This concept is simple but crucial for the later procedure. Based on the selected over atoms, the second procedure accumulates weighting coefficients for each subject, respectively, to obtain a new weight for each subject. The subject with the new maximum weight is regarded as the recognition result.

The main steps of OAOMP are summarized as follows:

1) Set $\Psi = [\psi_1, \psi_2, \dots, \psi_K]$ as a matrix of the training images for K subject, and a testing image $\mathbf{y}$ as input data.

2) Repeat OMP procedures K' times to obtain K' atoms.

3) Compute the new weight $w_i(\mathbf{y}) = \sum_{j=1}^{n_i} \alpha_j^{(i)}$ of each fish, respectively.

4) Assign the maximum weight $\mathcal{w}(\mathbf{y}) = \arg\{\max_i w_i(\mathbf{y})\}$, and label $\mathbf{y}$ by identity($\mathbf{y}$) = $\mathcal{w}(\mathbf{y})$.

B. Fish Identification Method

The fish identification verifies whether the testing image $\mathbf{y}$ is one of the fish species in the database, which is counted as valid identification, or if it is a new fish species, which is counted as invalid identification. This helps biologists to gain a greater understanding of the fish population in the area of interest. OAOMP can also be used to implement fish identification. A valid testing image should have sparse representation whose signification coefficients concentrate mostly on the correct subject, whereas an invalid testing image has coefficients spread widely among multiple subjects. Based on this concept, two identification rates are defined: valid identification rate (VIR) and invalid identification rate (IIR). High VIR means the testing image is one of the fish species in the category database, while high IIR represents the testing image that is a new fish species that does not belong to any fish species in the category database. The identification rates are computed as follows:

1) Set the number of valid testing images z_v and the number of invalid testing images z_e as input data.

2) Implement OAOMP method to obtain the maximum weight $\mathcal{w}(\mathbf{y})$ of each fish $\mathbf{y}$.

3) Compute identification probability value $p^{(i)} = \frac{\mathcal{w}(\mathbf{y})}{\sum_{i=1}^{K} \alpha^{(i)}}$.

4) Assign a threshold $\mathcal{T}$, and compute VIR using z_v and IIR using z_e.

VIR $= \frac{c_v}{z_v}$, where c_v is the number that $p^{(i)} > \mathcal{T}$ and the valid testing image of a fish species (i) is correctly classified to the fish species (i) in the category database.

IIR $= \frac{c_e}{z_e}$, where c_e is the number that $p^{(i)} < \mathcal{T}$.

IV. Experimental Results

Performance was evaluated for the proposed method, OAOMP, in a fish category database and the popular Extended Yale B face database [19]. PCA (eigenfaces) and LDA (fisherfaces) were used for feature extraction, respectively. A comparison was done of reconstruction performance and run time of OAOMP with existing reconstruction methods such as BP-related methods, OMP, CoSaMP, SP and ROMP. All experiments were run on a PC with CPU i5-3570 at 3.4 GHz, 8GB RAM with Windows 7 using MATLAB 7.5.0.

A. Fish Category Database

The fish category database consists of 25 fish species, and each species is described by 40 fish images, which results in a total of 1000 fish images. Each image has 160 row pixels and 120 column pixels, recorded in a JPEG file format. The total 40 fish images of subject 1 are illustrated in Fig. 2 as an example. As for each species of fish, 20 images were randomly selected for training, while the remaining 20 images were utilized for testing. All reconstruction algorithms were implemented over all species and repeated 10 times to obtain a stable average value. The eigenfaces and fisherfaces are adopted for feature extraction, and the first d values of the features were selected to form a feature space as well as represent the features of the image. Recognition rates were computed with the feature space dimensions d = 50, 100, 150, 200, 250, respectively. Table 1 shows the recognition rates of all methods using eigenfaces for feature extraction and the bold values indicate the best recognition rates: (1) PD, (2) SRC-RES, (3) SRC-MP (rank=20), (4) OMP, (5) CoSaMP, (6) SP, (7) ROMP and (8) OAOMP ($K' = K$+5). The curves of recognition rate versus the dimension of features are illustrated in Fig. 3.

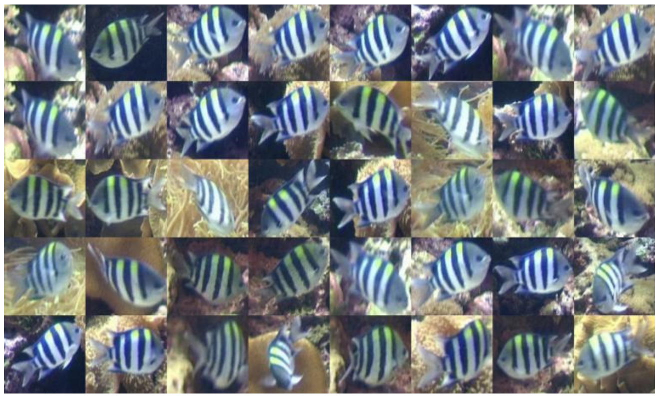

Fig. 2. An example of total 40 fish images of subject 1.

TABLE I. Recognition Rates (%) in Fish Category Database Using Eigenfaces

d	50	100	150	200	250
(1)	81.0	78.2	77.4	78.8	75.4
(2)	83.2	**82.0**	**81.6**	**82.4**	**82.6**
(3)	**83.8**	81.2	80.4	79.4	78.2
(4)	69.4	74.2	76.2	77.6	78.2
(5)	42.8	53.2	59.4	61.0	60.8
(6)	45.6	55.8	58.9	61.5	62.8
(7)	48.4	62.2	64.8	68.8	68.2
(8)	70.0	76.2	80.6	81.6	81.2

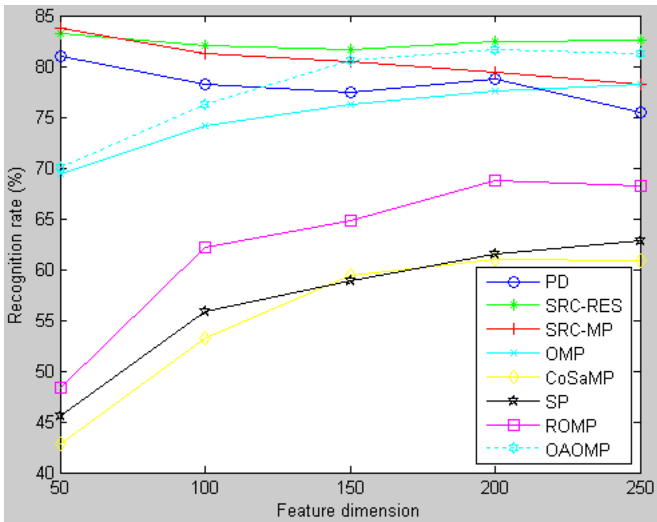

Fig. 3. Recognition rates of all methods versus feature dimension in fish category database.

Table 2 shows the recognition rates of all methods using fisherfaces for feature extraction and the bold values indicate the best recognition rates: (1) PD, (2) SRC-RES, (3) SRC-MP (rank=20), (4) OMP, (5) CoSaMP, (6) SP, (7) ROMP and (8) OAOMP ($K' = K$+5).

TABLE II. RECOGNITION RATES (%) IN FISH CATEGORY DATABASE USING FISHERNFACES

d	50	100	150	200	250
(1)	72.8	75.0	77.4	76.6	76.8
(2)	**80.0**	**81.0**	**827.2**	**80.6**	**80.2**
(3)	78.0	80.4	80.8	79.2	78.2
(4)	72.0	72.6	76.4	76.4	76.2
(5)	65.0	72.8	75.2	72.4	72.6
(6)	54.6	65.8	70.2	71.5	72.8
(7)	48.4	62.6	66.0	68.2	68.2
(8)	65.4	77.2	80.2	79.6	79.8

The run time of all methods was also compared. Table 3 shows the run time (s) of all methods using eigenfaces for feature extraction with feature space dimensions d = 250: (1) PD, (2) SRC-RES, (3) SRC-MP (rank=20), (4) OMP, (5) CoSaMP, (6) SP, (7) ROMP and (8) OAOMP ($K' = K$+5).

TABLE III. RUN TIME (S) IN FISH CATEGORY DATABASE USING EIGENFACES

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0.1443	0.3747	0.3738	0.0062	0.0059	0.0019	0.0040	0.0075

The experimental results show that the recognition rates of BP-related methods are superior to MP-related methods. The recognition rates of OMP are better than other MP-related methods. Moreover, our proposed OAOMP method obtains a better recognition rate than OMP. The experimental results also show that the run time of MP-related methods are shorter than BP-related methods, while SP has the shortest run time.

OAOMP utilizes an over-atoms concept to obtain over atoms. This study also estimated the influence of over-atoms. Different K' were assigned to compare recognition rates. Table 4 shows recognition rates with different K' where eigenfaces are used for feature extraction with feature space dimensions d = 250. The experimental results showed that the larger K', the higher the recognition rate when K' is in a certain range.

TABLE IV. THE RECOGINTION RATES (%) WITH DIFFERENT K'

$K' = K$	$K' = K$+5	$K' = K$+10	$K' = K$+15	$K' = K$+20
78.6	81.2	82.0	82.2	81.6

For fish identification, 30 fish images were randomly selected for training, while the remaining 10 fish images were used for testing. The 10 testing images were used, as valid fish images for calculating VIR. Furthermore, 25 new species of fish, with 10 images for each species, were collected as invalid fish images, to calculate IIR. Table 5 shows the VIR and IIR of OAOMP ($K' = K$+5) using eigenfaces and fisherfaces for feature extraction: (1) OAOMP-VIR (eigen), (2) OAOMP-IIR (eigen), (3) OAOMP- VIR (fisher), and (4) OAOMP- IIR (fisher).

TABLE V. IDENTIFICATION RATES (%) IN FISH CATEGORY DATABASE

d	50	100	150	200	250
(1)	80.0	84.0	88.0	84.0	92.0
(2)	76.0	80.0	88.0	84.0	88.0
(3)	60.0	68.0	76.0	80.0	84.0
(4)	72.0	76.0	80.0	88.0	84.0

Most of the VIR and IIR were over 80%, which implies that OAOMP was able to successfully classify valid testing fish images for known species of fish with a high degree of accuracy. Moreover, our method also efficiently identifies invalid testing fish images as new fish species.

B. Extended Yale B Face Database

In order to demonstrate that the proposed method and existing reconstruction algorithms have good reconstruction performance in pattern recognition, a popular and widely used face database, Extended Yale B, was utilized to test the performance of these reconstruction algorithms.

The Extended Yale B database has about 2,500 images of 39 different individuals. Thirty-four individuals were used because there are some missing images. Our database consisted of 2,108 faces that were cropped and normalized images of 192 rows and 168 columns in a PGM file format. There were 34 persons that individually contributed 62 frontal-images captured under various laboratory-controlled lighting conditions. The first 32 images of individual 1 are shown in Fig. 4. As for each subject, 31 images were used for training and the remaining 31 images for testing were randomly selected.

Fig. 4. An example of 32 face images of the 1st individual in the Extended Yale B face database.

Recognition rates were computed with feature space dimensions d = 50, 100, 150, 200, 250, respectively. Table 6 shows the recognition rates of all methods using eigenfaces for feature extraction and the bold values indicate the best recognition rates: (1) PD, (2) SRC-RES, (3) SRC-MP (rank=20), (4) OMP, (5) CoSaMP, (6) SP, (7) ROMP and (8) OAOMP ($K' = K$+5).

TABLE VI. Recognition Rates (%) in Extended Yale B Face Database Using Eigenfaces

d	50	100	150	200	250
(1)	92.69	95.73	96.11	96.20	96.11
(2)	94.50	96.58	96.49	97.06	97.34
(3)	**95.64**	**97.25**	**97.63**	**97.63**	**97.63**
(4)	77.89	92.69	95.26	95.45	95.64
(5)	62.81	80.93	87.86	90.32	92.13
(6)	42.88	81.50	88.33	89.85	91.84
(7)	46.96	77.42	87.76	90.13	92.60
(8)	80.93	94.31	96.20	96.58	97.06

Table 7 shows the recognition rates of all methods using fisherfaces for feature extraction and the bold values indicate the best recognition rates: (1) PD, (2) SRC-RES, (3) SRC-MP (rank=20), (4) OMP, (5) CoSaMP, (6) SP, (7) ROMP and (8) OAOMP ($K' = K$+5).

TABLE VII. Recognition Rates (%) in Extended Yale B Face Database Using Fishernfaces

d	50	100	150	200	250
(1)	96.02	96.96	96.49	96.39	96.49
(2)	97.53	97.82	**97.82**	**97.53**	**98.29**
(3)	**97.82**	**98.01**	97.72	97.34	97.63
(4)	96.39	96.30	96.02	95.54	96.02
(5)	86.15	91.46	94.78	94.78	95.26
(6)	79.70	91.08	94.97	95.45	95.07
(7)	68.31	91.08	94.97	95.16	95.73
(8)	97.72	97.44	97.34	96.77	96.77

V. Conclusion

This study presented and analyzed numerous reconstruction algorithms in compressive sensing, such as basic pursuit, orthogonal matching pursuit (OMP), compressive sampling matching pursuit, subspace pursuit, and regularized OMP. Based on OMP, an over-atoms accumulation OMP (OAOMP) method was proposed to improve reconstruction performance. OAOMP included two procedures: picking over atoms, and accumulating the weighting coefficients of each subject to assign as new weights. OAOMP was implemented for fish recognition and identification in a fish category database which was constructed from a real-world underwater stream system in Taiwan. OAOMP was evaluated and compared with existing reconstruction algorithms in terms of recognition rates, identification rates and run time. The experimental results showed that in general BP-related methods had better recognition rates than MP-related methods under the same dimensionality, while MP-related methods had shorter run times than BP-related methods. Moreover, OAOMP was able to achieve higher accuracy than OMP and other MP-related methods.

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