GBRAMP: A generalized backtracking regularized adaptive matching pursuit algorithm for signal reconstruction

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Abstract： In order to resolve the problem of excessive processing time and inadequate accuracy caused by existing algorithms in robot vision image reconstruction, a block variable step size adaptive compression sensor reconstruction algorithm is proposed. The algorithm integrates the regularized orthogonal matching pursuit technique in a seamlessly efficient manner to obtain consistent and accurate signal reconstruction outcomes. To apply this technique, a set of selected atoms is initialized by setting fuzzy threshold. Subsequently, inappropriate atoms are excluded, and an iterative procedure is initiated to update the set so as to approximate the signal sparsity in a stepwise fashion. In comparison with commonly used algorithms, the proposed algorithm achieved the lowest signal recovery and reconstruction error. Findings from this study indicate that our proposed hybrid paradigm may lead to positive advancement towards the development of intelligent robotic vision systems for industrial applications.

Keywords: Compressing sensing, Signal reconstruction, Matching pursuits, Sparsity, Reconstruction algorithm.

1. Introduction

Intelligent robot vision systems are multifunctional automated mechanical agents with capabilities to sense their environment, make decisions autonomously, provide control, and perform multiple tasks [1]. The rapid development of robotic technology began in the late 1950s when there was massive need for automation across different emerging industries. In recent years, intelligent robot technology has been widely utilized in various fields such as driverless cars, object detection and tracking in crowded environments, and defense intelligent home services [2-3]. In principle, a robot vision system integrates a set of a sensors, (a combination of camera hardware and computer programs) that enables the device to process visually perceived data in a manner that would allow proper interpretation of its content [4-8]. In such applications, the sensors are mostly designed to replicate the abilities of the human vision system using intelligent algorithms embedded into electronic devices [9]. In other words, the vision sensors are configured to acquire images, convert the sampled signals into digital image formats, and then extract reproducible characteristic signals through the integrated algorithm. Interestingly, it has been reported that such robotic vision systems could judge the scene in its environment independently and control its own actions in a seamlessly efficient manner. Meanwhile, real-time aspects and high efficiency of image signal sampling play important role in determining the overall performance of the robot vision system.

Modern-day robots are designed to operate in a structured environment. Due to the complexity and unpredictability of the external environment and the limitations of existing vision systems, current intelligent robots are unable to completely achieve their intended objectives [10-13]. In addition, unlike the for human vision, it is difficult for a robotic system to track and detect multiple objects simultaneously [9]. For this reason, much related research has focused on improving the performance of robot vision systems (particularly remotely controlled systems) by utilizing only a small percentage of the available image signal. If robotic vision systems are to operate efficiently and perform well in an unstructured environment, they require a great deal of intelligence and flexibility.

In developing a robotic vision system, it is often necessary to carry out remote transmission after data processing and storage, which greatly increases the overall operation cost. In the past, developers have tended to compress the data representing signals, leading to loss of big data samples [10]. At present, intelligent robot vision systems are based on traditional Nyquist sampling techniques. As a consequence, robots are slow to respond and cannot accomplish many tasks at a time. In addition, as sampling frequency is high and the amount of sampling data is very large, the computation process is very complex [12, 14]. In 2016 Donoho proposed a framework for compressed sensing of an object [14] to address this problem. The theory behind this approach consists of three parts: sparse signal; design of measurement matrix; and a reconstruction algorithm. The theory assumes that objects and images have sparse representation, which can be achieved using an orthogonal transform basis and an over-complete dictionary.

The traditional orthogonal transform basis includes discrete wavelet transform and discrete cosine transform. Since the basic shape of atoms in these transforms is fixed and scarce, the sparsest representation of an image cannot be achieved. Because of this problem, the study of flexible and efficient sparse bases has become a leading research direction in the recent years. One of the proposed solutions in this direction uses training algorithms such as MOD [15] and KSVD [16] [17]. These training algorithms usually involve sparse coding and dictionary updating which cannot be easily optimized, particularly during real-time usage.

Compressed sensing reconstruction algorithms proposed in the past include convex optimization [18], greedy class reconstruction module, and Bayesian reconstruction module [19]. Although the convex optimization algorithm has good reconstruction effect, it takes more time to reconstruct than the greedy class reconstruction approach. Meanwhile, the greedy class reconstruction algorithm has been widely adopted because of its fast computation and simple structure. These algorithms are based on the elements of the transform matrix (the *dictionary*) that best matches the signal during iteration.

Commonly used greedy algorithms include: Matching Pursuit (MP) [20], Orthogonal MP (OMP) [21], Regularized Orthogonal OMP (ROMP) [22], and Generalized Orthogonal Matching Pursuit (gOMP) [23]. These algorithms rely on sparsity knowledge for accurate reconstruction.

In many applications where the sparsity can be unknown, sparse adaptive MP (SAMP) [24] and regularized adaptive MP (RAMP) [25] are preferred as they can reconstruct the original image more accurately. In order to address, the need for both fast convergence and high reconstruction accuracy under unknown sparsity, in this paper we propose a hybrid algorithm called generalized backtracking regularized adaptive matching pursuit (GBRAMP). Our algorithm will contribute towards the realization of accurate identification of support sets in robot vision systems.

Specifically, based on the reconstruction of unknown sparsity signals, we propose a generalized backtracking regularized adaptive matching pursuit algorithm that utilizes a variant of the ROMP algorithm to exploit the advantages of regularization techniques towards fast and effective atom selection in combination with a backtracking screening approach to estimate sparsity. We give experimental results which via a verify the performance of the proposed hybrid method and compared its performance with existing methods. In particular we compare the performance of our algorithm with that of existing reconstruction algorithms, including: OMP, ROMP, StOMP, Subspace pursuit (SP), Compressive sampling matching pursuit (CoSAMP) and gOMP.

In summary, the contributions of this study are threefold. First, a generalized backtracking regularized adaptive matching pursuit algorithm based on the reconstruction of an unknown sparsity signal, that exploits the advantages of regularization technique towards effective selection of atoms in combination with backtracking screening. Second, validation of the performance of the proposed hybrid method compared to the existing reconstruction algorithms: OMP, ROMP, StOMP, Subspace pursuit (SP), the Compressive sampling matching pursuit (CoSAMP) and gOMP. Third, discussion of how the proposed hybrid paradigm may lead to positive advancement towards the development of intelligent robotic vision systems for industrial applications.

This paper is organized as follows. We first introduce the background of compressed sensing and signal reconstruction in Section 2, then the proposed GBRAMP algorithm in Section 3.

The experimental setup is also given in Section 4. Then, the performance of the proposed algorithm was investigated in comparison with the other existing reconstruction algorithms in Section 5. Finally, the paper is concluded in Section 6.

2. Compressed sensing and signal reconstruction

Compressed sensing is a collection of signal processing techniques used for signal representation from a small number of measurements. In principle, a typical compressed sensing-based problem could be modeled as follows. Suppose $\boldsymbol{x} \in \mathbb{R}^{\boldsymbol{N}}$ is a one-dimensional signal of length ***n*** and sparsity ***k***, where ***k<<n**,* the measured value *y* of length ***m*** is obtained by means of a measurement matrix ***Φ*** of $\boldsymbol{m} \times \boldsymbol{n}$**,** which is expressed as in (1):

$$y = \Phi x \tag{1}$$

On the other hand, the sensed signal ***x*** may not itself be sparse, but it may be sparse on a certain basis, that is ***x = Ψs***, where ***s*** is the sparse vector and ***Ψ*** is the sparse matrix. Therefore, the expression in equation (1) could be re-represented by equation (2) as follows:

$$y = \Phi\Psi s \tag{2}$$

It is worth noting that the problem of compressed sensing-based reconstruction is mainly aimed at recovering the original sparse signal ***x*** from the measured value ***y*** of ***m < n***, and usually if **m <** ***n***, the inverse problem is ill-posed. However, the sparsest solution expressed in equation (2) could be obtained by solving the constrained optimization problem which is expressed as follows in equation (3):

$$min\|s\|_0, subject\ to\ y = \ \Phi\Psi s \tag{3}$$

where $\|s\|_0 = \sum_{j=1}^{n}|s_j|^0$; and ***s*** is the number of nonzero components. Since Equation (3) represents a non-convex optimization problem that requires quantifying a subset of the dictionaries and identifying the smallest subset representing signal ***x*** which increases the signal size exponentially. According to a major result of compressed sensing theory, if ***x*** is ***k***-sparse, the waveforms are independent and identically distributed randomly, and the number of measurement ***M***, satisfies the condition in (4)

$$M \ \geq c \cdot k \cdot \log\left({}^{n}/_{k}\right) \quad ; c = small\ positive\ constant \tag{4}$$

Therefore, the signal $\boldsymbol{x}$ can be reconstructed by solving the convex problem in (5).

$$min\|s\|_1, subject\ to\ y = \Phi\Psi s \tag{5}$$

where Equation (5) is known as basic pursuit.

The major objective of a reconstruction algorithm is to maximize the reconstruction of the original signal using low-dimensional data observed by the measurement matrix. Although the convex optimization technique (basic pursuit) has a good reconstruction effect, it is not practical to apply due to high computation time requirements. At present, among the three most adopted groups of reconstruction algorithms, greedy algorithms are the most studied in compressed sensing due to their fast reconstruction and low computation capability. They can provide a solution to the reconstruction problem in a step-by-step iterative manner that can be easily understood. However, more attention is paid to the sparse unknown reconstruction for greedy algorithms, because it does not require the precondition of known signal sparseness. Hence this form of application is more common.

Commonly used greedy algorithms include: SAMP and RAMP. They approximate sparseness by setting an initial step and expanding the support set in a stepwise manner. The backtracking adaptive orthogonal matching pursuit algorithm reconstructs the unknown sparseness signal by backtracking detection. Recently a forward-backward tracking algorithm has been proposed to better estimate sparsity by iteratively accumulating the difference between the forward and backward steps. The energy-based adaptive matching pursuit algorithm increases the sparsity level gradually according to the increase of the iteration residual energy. In addition, the difference-based sparsity adaptive reconstruction algorithm uses the rate of change between the measurement matrix and the residual inner product elements to approximate the sparsity adaptive. To overcome these limitations, a generalized backtracking regularized adaptive matching pursuit algorithm (GBRAMP) is proposed in this study.

3. The proposed algorithm

In this section, we briefly introduce the existing ROMP algorithm, then give a detailed description of our proposed generalized backtracking regularized adaptive matching pursuit algorithm (GBRAMP algorithm). The ROMP algorithm is an improved algorithm of the conventional MP and OMP algorithms, and its basic operational principle is driven by the OMP algorithm. It uses a regularization method to select several qualified elements per iteration to quickly classify the elements, thus shortening the time taken for signal reconstruction. The execution process of the ROMP algorithm is stated as follows:

Step 1:

Atomic selection: Based on the OMP algorithm, the ROMP module selects an element by using the absolute value of the inner product between the elements of the measurement matrix $\boldsymbol{\Phi}$ and residual $\boldsymbol{r}$, to calculate the correlation coefficient $\boldsymbol{u} = <\boldsymbol{\Phi}, \boldsymbol{r}>$. After that, $\boldsymbol{K}$ atoms (i.e., column atoms corresponding to the largest $\boldsymbol{K}$ value in $\boldsymbol{\Phi}$) matched with residual values are put into set $\boldsymbol{J}$.

Step 2:

Regularization: According to the measurement of the correlation coefficient $|\boldsymbol{u}(\boldsymbol{i})| \leq 2|\boldsymbol{u}(\boldsymbol{j})|\ \boldsymbol{i}, \boldsymbol{j} \in \boldsymbol{J}$, elements in the set are divided into groups. The set of elements with the largest correlation coefficient are input into group $\boldsymbol{J_o}$.

Step 3:

Residual updating: By estimating the signal using the least squares method for atoms in the support set, $\boldsymbol{J_o}$ is added to the support set of the last iteration and the residual value is updated with the obtained signal.

From the first step of the algorithm execution procedure, it can be seen that the ROMP algorithm requires that the sparsity of the signal is known. Hence, when reconstructing image signals with unknown sparsity, the reconstruction effect can be abjectly affected by the necessity of estimating the sparsity value. In addition, although the ROMP algorithm uses the regularization principle to screen the $\boldsymbol{K}$ atoms initially selected, with the increase of iterations the support set inevitably contains some incorrect atoms. For this reason, it is necessary to introduce backtracking to update the support set.

The proposed GBRAMP algorithm is aimed at addressing the above shortcomings of the ROMP algorithm. The basic goal of the proposed GBRAMP algorithm is to maintain the regularization process whilst at the same time addressing the limitations of the existing methods. In the proposed method, the algorithm adaptively chooses atoms by setting a fuzzy threshold to increase the randomness of the number of atoms. Then, a set of atoms whose indices have the largest energy is selected and put into the set $\boldsymbol{J_0}$ using the regularization method. After merging with the support set of the previous iteration, the non-zero coefficients of the signal are calculated using the least squares method. Finally, the process of retrospectively updating and expanding the support set to approximate the sparsity is carried out.

The maximum coefficient ***Θ*** of the index corresponding to the non-zero coefficient in $\boldsymbol{J_0}$ is found, and all the indices with a non-zero coefficient greater than ***β.Θ (0 < β < 1)*** are put into the support set ***I***. One of the major purposes of the proposed method is to find the non-zero coefficients of the signal. If the coefficients of previously selected atoms are smaller than the threshold value ***β.Θ***, the previously selected atoms may be incorrect and so are deleted by the retrospective method. In this way, cyclic iteration is carried out to complete the reconstruction of the signal when the stopping condition is reached. The algorithm terminates when the residual value is less than $\boldsymbol{\varepsilon}$. The specific implementation steps of the backtracking regularization adaptive matching pursuit algorithm integrated into the proposed method is presented in **Figure 1**.

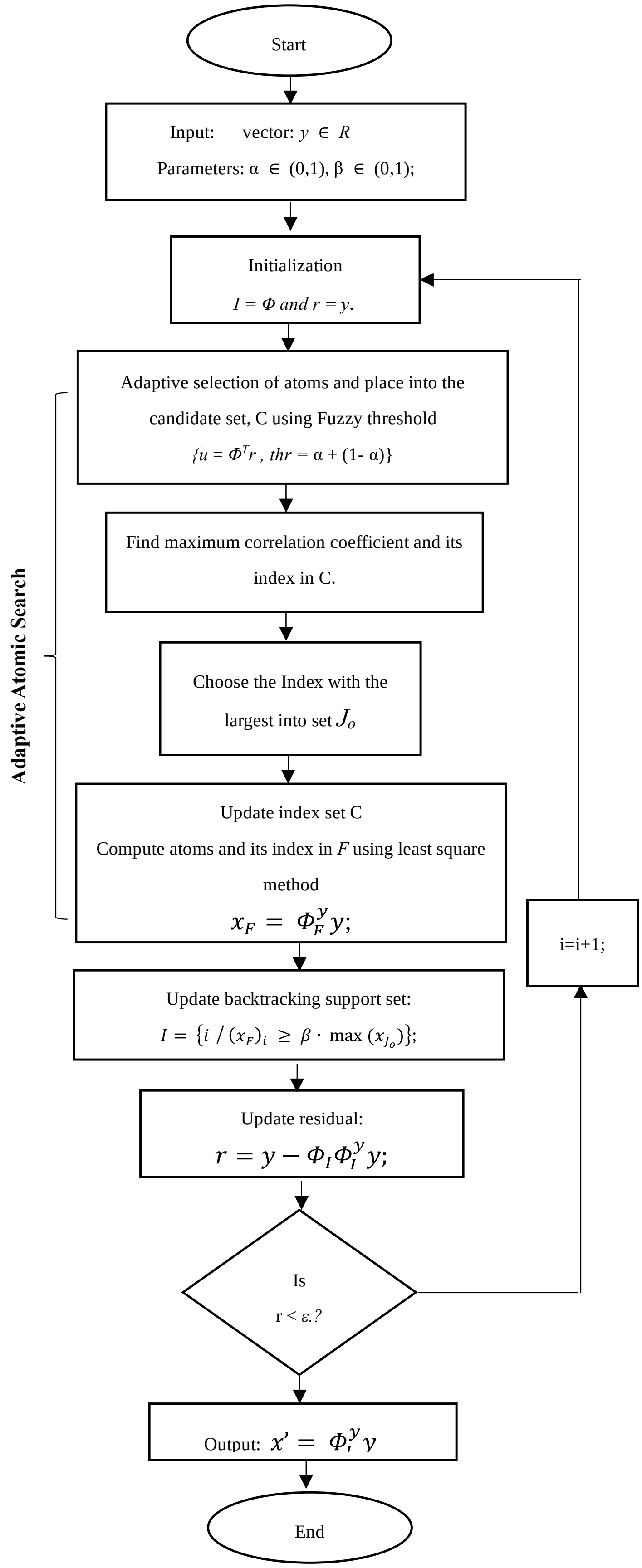

Figure 1. Flowchart diagram of the proposed algorithm, generalized backtracking regularized adaptive matching pursuit reconstruction algorithm **(**GBRAMP**)**

In the above process, the algorithm adaptively selects the initial atoms based on the fuzzy threshold, and the number of atoms is determined by the parameter $\boldsymbol{\alpha}$. When the value of $\boldsymbol{\alpha}$ is small, the number of atoms selected in each iteration is large, and the algorithm executes faster. Unlike the RAMP algorithm that uses the regularization method to select the group of atoms with the most energy, our algorithm employs a retrospective approach that helps to gradually expand and update the support set. The number of atoms to be updated in each iteration is controlled by a constant beta parameter. This characteristic of our algorithm overcomes the shortcomings of the ROMP and SP algorithms that require known sparsity. It also allows us to overcome a limitation of the non-backtracking RAMP algorithm for which, once selected, incorrect atoms cannot be eliminated, thus affecting the step size.

Another example of the proposed algorithm is that it is based on the characteristics of the estimated signal and iterative reconstruction without being affected by a sparseness value estimated purely on experience. The reconstruction accuracy and computational complexity of the proposed algorithm are balanced by adjusting $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. Although this algorithm has these advantages, its running time is slightly longer than that of the RAMP algorithm. This is due to the addition of backtracking when evaluating sparsity.

4. Experiment setup

Performance comparison between the proposed algorithm and other existing reconstruction algorithms was carried out using different simulation models. The experimental procedure is divided into two parts: in the first we use a one-dimensional sparse signal and in the second we extend the approach to a two-dimensional approximate sparse signal, i.e., the image signal. The proposed algorithm was implemented using MATLAB 2016b software running on a computer system with the following configuration: Intel (R) Core (TM) i7-2670QM CPU, frequency 2.20GHz, and memory 8GB.

The measurement matrices involved in this paper are all Gauss random matrices while the reconstruction algorithms considered for the comparison are OMP, SP, CoSAMP, ROMP, SAMP, gOMP and the proposed GBRAMP algorithm. In each case we set the maximum number of iterations ***M*** as well as the residual termination condition as *norm* ***(r)*** **< 1e**$^{-6}$. In addition, for the RAMP and SAMP algorithms, an initial value of **3** was used for the recovery ratio is defined as:

$$Err = 1 - \frac{\|x - x'\|_2}{\|x\|_2} \tag{6}$$

The performance of the reconstruction algorithms was evaluated using the mean square error (MSE) metric described in (7)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{7}$$

where n is the length of the signal, Y_i is the original signal and $\hat{Y}_i$ is the reconstructed signal.

5. Results

In this study, the performance of the proposed algorithm was systematically investigated in comparison with the other existing reconstruction algorithms using a number of structured experiments. The ability of the proposed and previously proposed methods to reconstruct randomly generated dataset for several values of the ambient signal dimension N with fixed measurement value M, and sparsity K, was examined. It should be noted that for the signal selection, a Gaussian sparse signal with a length of N = 256 and a measured value of M = 128 was utilized. Analyses of the obtained results have been carried out based on different experimental designs, described below.

5.1. Probability of signal reconstruction across sparsity at constant measurement value

We first investigate the probability of exact signal reconstruction with respect to the signal sparsity ***K*** for a given value of ***M***. In this paper, the signal is said to be accurately reconstructed if the non-zero elements of the actual signal ***x*** and the recovery signal x' are in the same positions. Sparsity values ranging from 5 to 90 were chosen and for each value of ***K***, 100 simulations were performed. We note that the precise reconstruction probability and the computation time of the Gaussian sparse signal vary with the degree of sparsity. Reconstruction results for the different algorithms are presented in **Figure 2**, where the *x* and y axes represent the level of sparsity and probability of exact recovery, respectively.

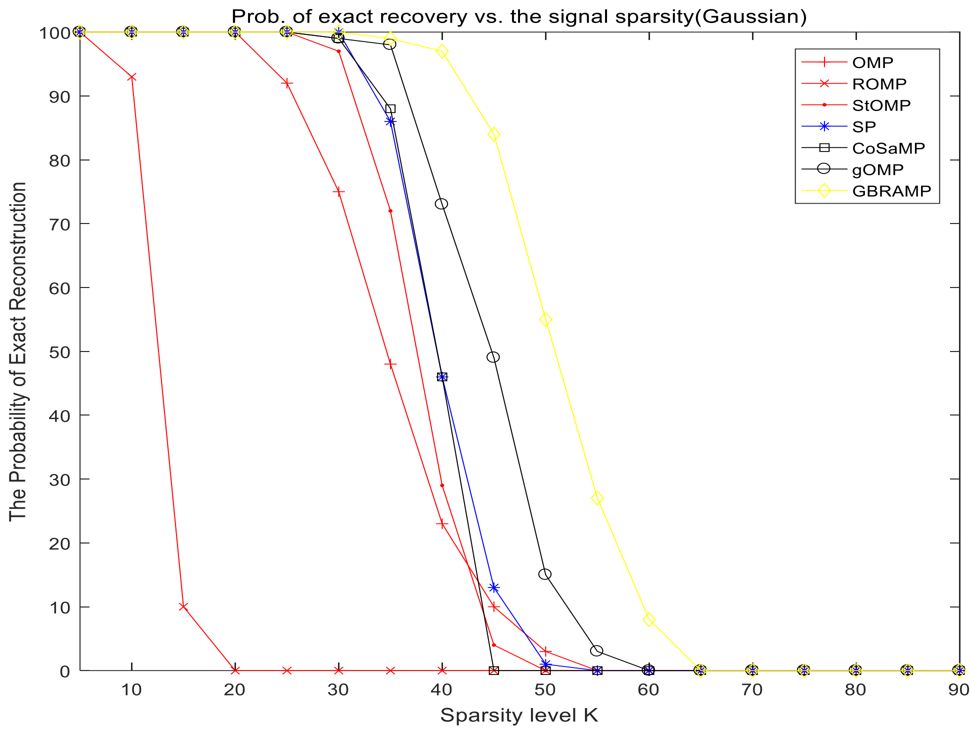

Figure 2. Exact recovery ratio performance as a function of sparsity K. Note: Signal length, N =256 and fixed measurement value, M= 128.

As shown in **Figure 2**, the GBRAMP algorithm is able to reconstruct the signal much better than the other algorithms, whilst at the same time achieving better sparsity. While the reconstruction effect of GBRAMP is better than all of the other methods, the gOMP algorithm performs better than OMP, SP, RAMP and ROMP for K<40. Although the signal could not be completely reconstructed for 40<K<90, the reconstruction effect of the GBRAMP algorithm is much better than for the other algorithms. Meanwhile, OMP and ROMP recorded the worst performance because they both deviated from the actual path of reconstruction when K<20 and K<30 respectively.

5.2. Probability of signal recovery across measurement value at constant sparsity

Using the same procedure as for the first experiment, we then examined the percentage of signal recovered against the number of measurements when the signal sparsity K is constant, using measurement values ranging from 55 to 100, and K =20. For each measured value, a signal of sparsity k was generated. In each case the proposed the sparse signal and the percentage of exact reconstruction was computed. The obtained results are presented **Figure 3**.

It can be seen that GBRAMP performs better than the other algorithms. In particular, GBRAMP was able to recover a good percentage of the sparse signal when M <=75. At M = 80, both GBRAMP and gOMP could recover 100% of the sparse signal. However, between the measured values of 80 to 90, gOMP signal recovery accuracy drops while that of the proposed GBRAMP method remains consistent. This observation shows that the proposed method is more stable and accurate at different measured values than the other algorithms.

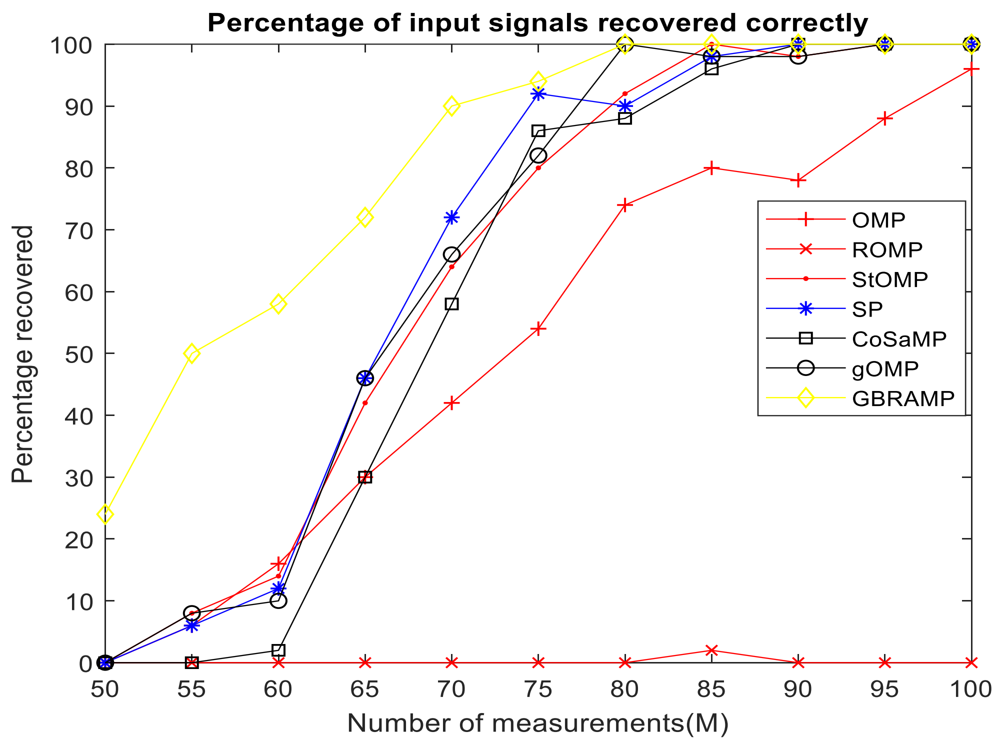

Figure 3. The percentage of signal recovered as a function of the number of measurements M in dimension N = 256 at a constant value of K = 20.

5.3. Evaluation of signal computation time across different sparsity values

From the results presented in **Figure 4**, it can be seen that the running time of GBRAMP is longer than that of other algorithms. This is because the GBRAMP algorithm incorporates an iterative technique that gradually approaches the sparsity value. It should be noted that, unlike the other algorithms, GBRAMP deletes incorrect atoms before each iteration by using backtracking. This increases reconstruction quality at the expense of increased running time. Generally, it can be observed that as the sparsity level increases, the computation time of all reconstruction algorithms increases (**Figure 4**).

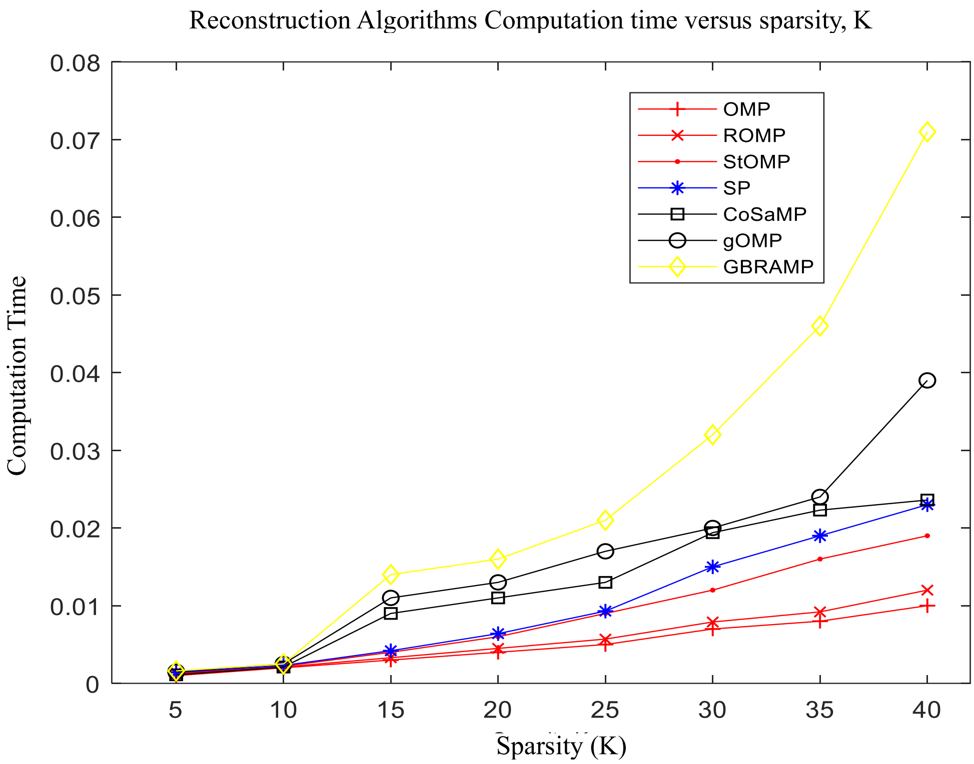

Figure 4. Comparison of the complexity of the proposed algorithm and the previous methods in terms of the computation time, which was defined as a function of sparsity, K.

5.4. Reconstruction of distorted single-dimensional sparse signal

In this experiment, we compared the recovery accuracy of the different algorithms when the original signal is contaminated with white Gaussian noise. More precisely, an additive white Gaussian noise of **10 dB** was introduced into the original sparse signal. Note that the power of the sparse signal was measured before the noise was added. **Figures 5 (a)** and **(b)** show the original sparse signal and the distorted signal, respectively. For each algorithm the reconstructed signal from the distorted sparse signal is shown in **Figure 6**. It is clear that in the presence of additive white Gaussian noise, GBRAMP was able to reconstruct the one-dimensional signals with better accuracy than the other algorithms**.**

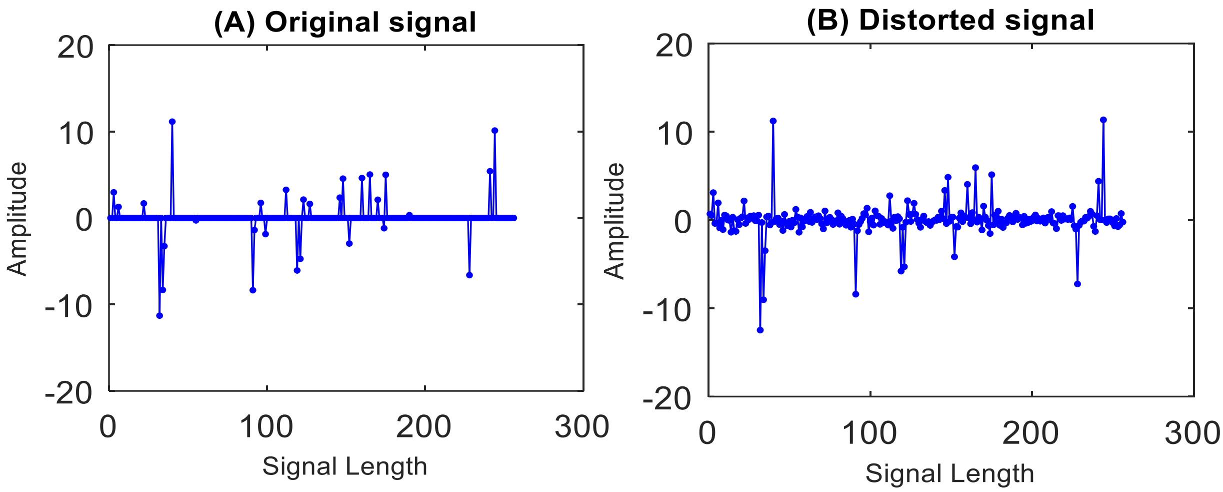

Figure 5: Representation of the originally generated signal (a), and the distorted version of the signal using additive white Gaussian noise

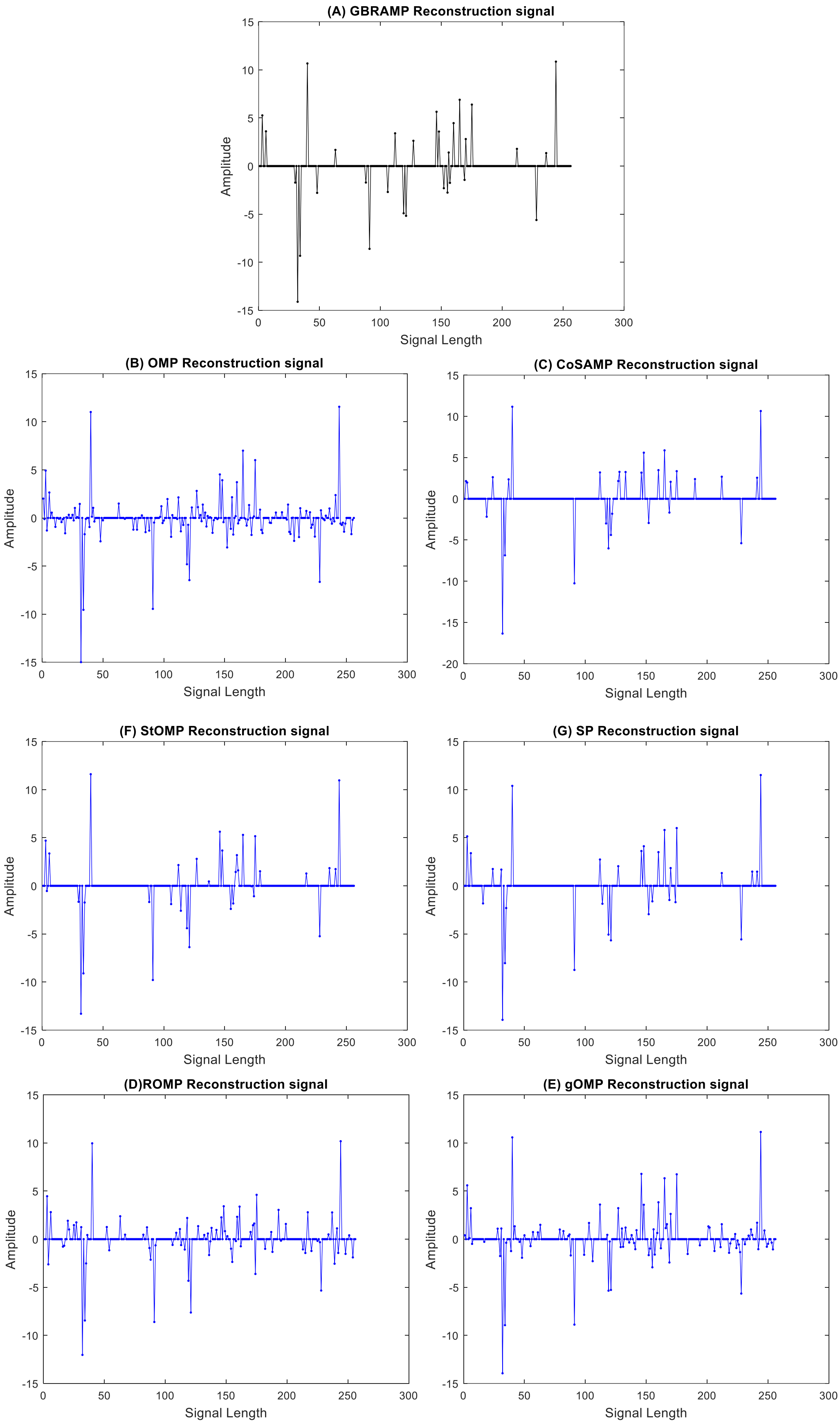

Figure 6: Exact signal recovery for the proposed GBRAMP method and the other considered algorithms when a 10 dB additive white Gaussian was introduced into the original signal

5.5. Sparse signal recovery error at different sparsity and measurement values

A further experiment was conducted to examine the recovery error rate of the proposed method compared to that of the other algorithms at different sparsity levels and measurement values. Note that this experiment was carried out to further validate our findings from the previous experiments. Table 1 presents recovery error rate results for all the reconstruction algorithms at different sparsity K levels when the value of M was set to 128. Table 2 presents the recovery error rate results for all the reconstruction algorithms at different measurement values when K was set to 20. It can be deduced from both (Table 1 and Table 2), that GBRAMP has the least signal recovery error followed by gOMP. These results further show the superiority of GBRAMP over the other methods in terms of accurate reconstruction of signals.

Table 1: Signal Recovery Error at different Sparsity K Levels when M=128

	Sparsity (K)									
Algorithms	10	20	30	40	50	60	70	80	90	100
OMP	8.55E-32	1.08E-04	8.32E-31	2.25E-04	0.788208	1.904589	2.581068	1.911486	4.541676	3.806002
ROMP	4.89E-32	0.090446	0.603218	0.617696	1.61684	5.666846	2.649431	4.329278	4.002725	5.664299
StOMP	4.69E-31	4.90E-31	5.39E-30	0.236549	0.602262	1.108991	1.964226	2.415417	2.992484	3.098453
SP	5.71E-31	1.56E-30	1.79E-30	5.71E-30	0.646583	2.947934	1.885343	3.25886	2.980691	3.90332
CoSAMP	7.28E-32	7.63E-31	3.46E-30	1.28E-28	2.094218	8.963196	2.9499	3.583188	4.004406	4.186434
gOMP	2.69E-31	9.51E-31	1.21E-30	3.40E-30	1.09071	1.855677	3.003511	1.652196	2.661278	5.681467
GBRAMP	**4.89E-33**	**5.57E-32**	**1.68E-32**	**5.00E-31**	**9.01E-3**	**0.105173**	**1.6244**	**1.148374**	**2.071809**	**2.717304**

Table 2: Signal recovery error at different measurement value when K=20

	Measurement value when K=20			
Algorithms	32	64	128	512
OMP	2.33E+00	2.01E-31	6.04E-31	4.07E-31
ROMP	7.90E-01	1.150267	0.627876	2.95E-31
StOMP	2.88E-01	3.76E-01	1.15E-30	5.73E-31
SP	7.74E-01	2.25E-01	6.53E-31	1.17E-30

CoSAMP	1.15E+00	1.20E+02	1.66E-30	6.58E-31
gOMP	1.47E+00	1.25E-02	4.21E-31	4.86E-31
GBRAMP	1.01E+00	1.24E-01	1.05E-31	2.90E-32

5.6. Percentage of sparse signal recovery at different sparsity K and measurement values

Finally, we investigated the performance of GBRAMP at different sparsity levels and measurement values when alpha was set to 0.5. We note that before carrying out this experiment we investigated the effect of using different values of alpha ranging from 0.1 to 1.0. We discovered that setting alpha to 0.5 allowed the sparse signal to be recovered correctly. Sparsity K levels ranging between 5 to 25 and measurement value of 0 to 250 were used for this experiment. The obtained results are presented in **Figure 7**. It can be deduced that the percentage of signal recovery increases with an increase in the measurement value. Furthermore, the proposed algorithm was able to recover the sparse signal accurately when 45 < M < 120 for different sparsity levels.

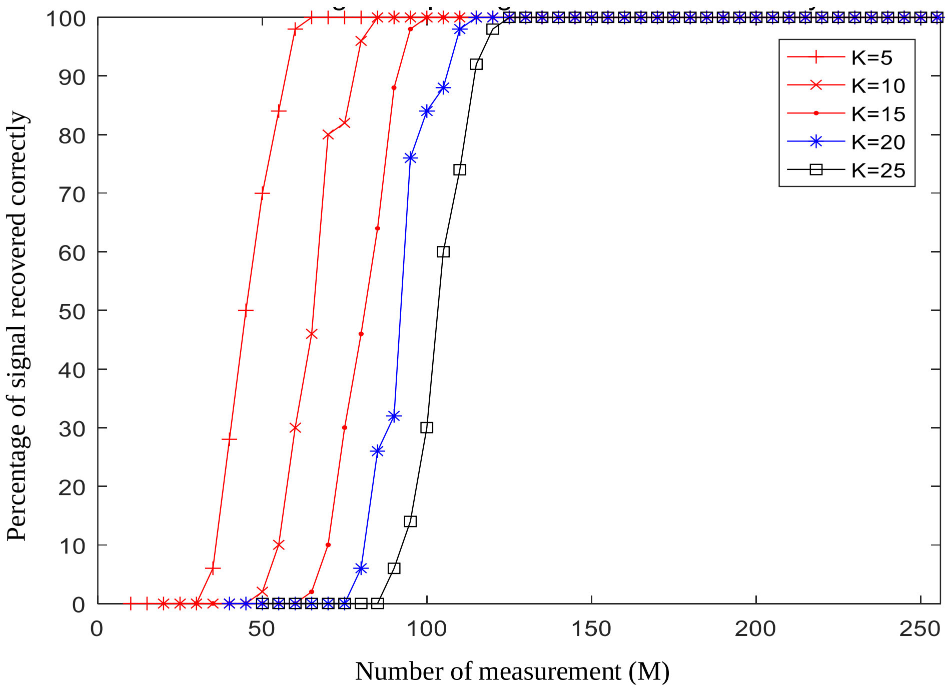

Figure 7. The percentage of recovered signals with respect across different measurements and sparsity

6. Conclusion

This paper proposes a generalized backtracking regularized adaptive Matching Pursuit (GBRAMP) method to overcome limitations of existing regularized orthogonal matching pursuit algorithms for signal reconstruction in intelligent robotic vision systems. The operational principle of the proposed GBRAMP method is based on the adaptive selection of the required atom set by setting a fuzzy threshold, then regularizing the selected atoms. Subsequently, a backtracking strategy is used to detect incorrectly selected atoms, which are then are omitted from the updated support set.

The proposed algorithm was investigated using a number of evaluation criteria and its performance was compared to some commonly used methods. Analysis of the experimental results revealed that the proposed method can effectively reconstruct the signal at different sparsity levels. Though the signal cannot be completely reconstructed at $40 < K < 90$, the reconstruction effect (e.g., percentage of signal recovered) of the GBRAMP algorithm compared more favorably to other utilized algorithms. Furthermore, the proposed method was able to recover a good percentage of the sparse signal (when $M <= 75$). A similar performance trend was observed in terms of signal reconstruction accuracy when the original signal was contaminated with additive white Gaussian noise and when the proposed method was compared to existing algorithms at different sparsity levels and measurement values. The reconstruction of the unknown sparse signal can be achieved with high accuracy and with relative ease compared to the existing methods. The obtained experimental results demonstrate that the proposed GBRAMP algorithm provides a useful tool for the reconstruction of signals in the context of intelligent robot vision systems.

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Conflict of interest statement

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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