International Journal of Scientific Engineering and Applied Science (IJSEAS) - Volume-1, Issue-4, July 2015
ISSN: 2395-3470
www.ijseas.com

SCALE ADAPTIVE DICTIONARY LEARNING

Ande Praveen[1],Dr.Y.Venkateswarulu[2]

[1]Mtech Student, CSE, Giet Engineering College, Rajahmundry, A,P, India
[2]Professor and HOD, Dept of CSE, Giet Engineering College, Rajahmundry, A,P, India

ABSTRACT

In numerous image handling assignments the lexicon learning has been broadly utilized. In a large portion of these systems, the quantity of premise vectors is either situated by experience or coarsely assessed observationally. In this paper we propose another Scale Adaptive Dictionary Learning (SADL) structure, which together gauges suitable scales and relating particles in a versatile manner as indicated by the preparation information, without the need of earlier data. We outline a molecule tallying capacity and build up a solid numerical plan to tackle the testing improvement issue. Broad trials on surface and feature datasets show quantitatively and outwardly that our technique can appraise the scale, without harming the meager recreation capacity.

Index Terms—Dictionary learning, sparse coding, sparse representation, image restoration.

INTRODUCTION:

Meager lexicon learning [1] means to develop word references as indicated by particular information visual information. It offers climb to inadequate representation of pictures patches or feature volumes utilizing just a couple of particles and has gotten to be extremely prevalent in these years as it can be utilized in taking care of numerous picture preparing issues [2], [3], [4], [5], [6], [7].

A word reference contains numerous iotas as a rule. Its scale is exceptionally variable, going from hundreds to many thousands in diverse applications. Experienced designers require a couple of tryouts or fix it to a number s/he feels great with. For instance, in [1], [5], [8], the scale is situated by. In [9], three diverse word reference scales are tried.

As far as scale determination, past methodologies are either tedious or obliging broad learning. It is particularly awkward when managing applications that include transforming expansive scale information or realizing numerous lexicons in the meantime.

For instance, in surface combination composition information have distinctive word reference scales, which rely on upon how educational structures are. For the straightforward block surface, 23 word reference particles are sufficient to depict structure variety. Unexpectedly, for the "swarm" picture, its mind boggling examples lead to a lexicon with 189 iotas. These numbers are not natural for people to

International Journal of Scientific Engineering and Applied Science (IJSEAS) - Volume-1, Issue-4, July 2015
ISSN: 2395-3470
www.ijseas.com

be mindful of. In the event that the word reference scale can be dead set consequently amid enhancement, visual information can be prepared successfully without requiring broad human experience or earlier learning.

Bayesian scanty models [10] were created expecting to learn lexicons in a non-parametric manner. Construing lexicon scales is likewise achievable. At the same time, as pointed out in [11], these systems may not know whether the Bayesian model is proper or not for the information nearby. Further, they by and large take overwhelming computational expenses. Ramirez et al. [11] utilized the Minimum Description Length (MDL) standard to gauge lexicon size utilizing a specification plan. It evaluates all conceivable lexicon scales from one to the most extreme quality permitted. At the point when the dormant word reference scale is extensive, this identification plan is not that proficient. Besides, both Bayesian meager [10] and MDL [11] models can't keep away from indistinguishable and fundamentally the same molecules hypothetically. In this paper, we propose a Scale Adaptive Dictionary Learning (SADL) strategy. Dissimilar to count in MDL [11], it is a brought together system to take in the scanty lexicon representation and focus the fitting number of particles all the while, which has a divergence lower destined for any two molecules hypothetically.

This paper is organized as follows. In Section 2, SADL are proposed. Section 3 discusses results and discussions. Conclusions are given in Section 4.

PROPOSED METHOD:

Word reference Compactness and Scale Adaptation: High lexicon conservativeness makes learnt iotas discriminative. There are methodologies, for example, [12], that add additional discriminative terms to achieve this objective. Yet these techniques still predefine the lexicon size, freely from the information close by. Our system can preferably catch this conservativeness property. We demonstrate in what takes after that it can dodge indistinguishable or very much alike iotas in word reference learning. We likewise demonstrate that the Euclidian separation between any two learnt iotas in our outcomes has a nonzero lower bound. These conditions have never been examined in this field. They are additionally not so much fulfilled in former models.
The two steps are referred to as dictionary update and dictionary selective sparse coding respectively.

A. Dictionary UpdateWe resort to the classical first-order projected stochastic gradient descent algorithm [16] to compute **D**. It updates **D** iteratively. In each iteration,

$$\mathbf{D} = \prod_{\mathcal{D}}[\mathbf{D} - \delta_t \nabla_{\mathbf{D}} \mathbf{L}(\mathbf{D})], \qquad (1)$$

where$\delta_t$is the gradient operator, and Π D represents the projector to refine the dictionary in set D.

B. SADL Framework Summary: In summary, starting with a random **D**, we apply Algorithm 1 In the inner iteration of {A,**T**}, when the energy

$$E_\rho(\mathbf{D}, \mathcal{A}, \mathbf{T}) = \frac{1}{n}\sum_{i=1}^{n}\{\frac{1}{2}\|\mathbf{D}\boldsymbol{\alpha}_i - \mathbf{x}_i\|_2^2 + \lambda\|\boldsymbol{\alpha}_i\|_1\} + \mu\sum_{j=1}^{k}[\rho\|\widehat{\boldsymbol{\alpha}}_j - \widehat{\mathbf{t}}_j\|_2^2 + \mathbf{I}(\widehat{\boldsymbol{\alpha}}_j)]$$

(2)reaches its limit, the system terminates. The final dictionary consists of atoms

International Journal of Scientific Engineering and Applied Science (IJSEAS) - Volume-1, Issue-4, July 2015
ISSN: 2395-3470
www.ijseas.com

$\{\mathbf{d}^*_j | II(t^*_j = 1\}$. The scale is automaticallyadaptive to input visual data.

Algorithm 1 Scale Adaptive Dictionary Learning (SADL)

input: input data $\{\mathbf{x}1, . . . , \mathbf{x}n\}$; regularization parameters λandμ

initializeρ = 1, t = 1; generating $\mathbf{D}0$ randomly.

repeat

$\mathbf{T}^0 = \mathbf{T}t\text{-}1$, $A^0 = At\text{-}1$;i= 0

repeat

with$\mathbf{T}^{i-1}$, solve for A^i

withA^i, solve for $\mathbf{T}^i$

i= i+ 1

until$E\rho(\mathbf{D}t\text{-}1,\mathbf{T}i,A^i)$ converge;

$\mathbf{T}t= \mathbf{T}^i$,$At= A^i$;

withAt,$\mathbf{D}t\text{-}1$, solve for $\mathbf{D}t$using gradient descentalgorithm [16];

$\rho \leftarrow 2\rho$, t = t + 1;

until$\mathbf{D}t$converge or $\rho > 10^5$

$\mathbf{D}^* = \mathbf{D}t$, $\mathbf{T}^* = \mathbf{T}t$

return atoms $\{\mathbf{d}^*j | I(b\mathbf{t}^*j) = 1\}$ for $\forall j = 1, . . . , k$.

Results analysis and discussions:

Convergence Analysis: In Algorithm 1, we increase ρ gradually in each iteration as shown in Fig. 1. This scheme, compared to fixing ρ to a large value, warms up the optimization, and has the effect to pull results out of local minima.

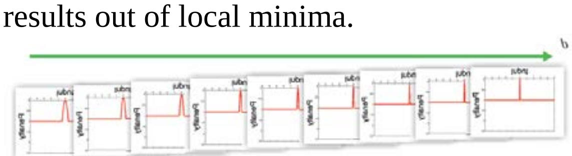

Fig 1: ρincreases gradually in iterations to make T(.) approach I(*).

We direct far reaching examinations to confirm our model. In subjective assess, we characterize "safe word reference" and "85% lexicon". Safe lexicons are prepared by means of the conventional technique [1], which are with twofold the quantity of molecules than those created in our strategy. On the off chance that our word references are correspondingly successful as these safe ones, our learnt lexicon is viewed as complete. In the mean time, we prepare lexicons with 85% of the size controlled by our system. We call them 85%-lexicons. In the event that diminishing 15% of the particles fundamentally increments inadequate recreation slips, it is evident that our assessed scale is near to the lower bound that a word reference needs to be with.

SURFACE EXPERIMENTS

Meager representation is extremely valuable in tackling numerous surface included issues, for example, composition in-painting, amalgamation, and grouping [13], [14]. We first utilize them to assess our system. All in all, structure intricacy of composition or the measure of data put away can be coarsely seen. For instance, in Fig. 2, the left most surface is evidently less intricate than the privilege generally ones. So the word reference size ought to increment in like manner. In our trials, we resize surface pictures to 400×400 pixels. Fixes in every picture are consistently tested with size 16 × 16 in a covering way. We look at the subsequent word reference scales and lead in-painting to assess our technique

(a) (b) (c) (d) (e) (f)

Fig 2: Sample texture Images

1) Performance with Different Starting Points: We use a random dictionary for initialization. Experiments have been conducted to evaluate how sensitive our

International Journal of Scientific Engineering and Applied Science (IJSEAS) - Volume-1, Issue-4, July 2015
ISSN: 2395-3470
www.ijseas.com

algorithm is to different starting points. For each texture in Fig. 6, we randomly generate 100 different initial dictionaries, starting from which we produce our results. Statistics are listed in Table I.

Table 1: Mean, Variance, Minimum, And Maximum Of 100 Estimated Scales Produced With Different Initialization For Each Texture Example

	(a)	(b)	(c)	(d)	(e)	(f)
Mean	21.9	40.9	62.9	74.9	80.5	1403.5
variance	0.19	0.13	0.22	0.14	0.15	0.16
minimum	24	45	65	79	85	105
Maximum	22	32	41	36	56	72

2) Parameter Setting: Two parameters λ and μ are permitted to shift in our technique. We demonstrate how results are affected in Tables II and III. These measurements show that our system is not immensely touchy to these parameters when they are sensibly situated and consequently can utilize altered values as a part of general. 3) Scale Adaption Evaluation: We apply our technique to a set of composition pictures in Fig. 2. Our trial results show the instinct that the left- and right-most lexicon sizes change a ton. For the straightforward block surface, 23 premise vectors are sufficient to portray structure variety, as indicated in Fig. 7. For the blossom picture, the composition has more points of interest. Its word reference measure in like manner increments to 76. At last for the swarm surface, in spite of the fact that its determination is little, the numerous subtle elements lead to a word reference with 189 particles, agreeing to our visual instinct. For every composition, we have 10, 000 preparation fixes; the normal preparing time for every surface is 5.90 minute

Table II: Scale Estimates under Different λon The Six Textures

λ	**(a)**	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**
0.1	21	39	65	73	81	101
0.2	21	39	65	73	81	101
0.3	21	39	65	73	81	101
0.4	21	39	65	73	81	101

Table III: Scale Estimates under Different μ on The Six Textures

μ	**(a)**	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**
0.0005	21	39	65	73	81	101
0.001	21	38	65	73	81	101
0.002	21	39	64	73	80	100
0.004	21	39	64	73	80	101
0.008	21	39	63	73	80	101

We contrast our SADL and conventional lexicon learning [9] that set the same scale to all lexicons for distinctive sub areas. For decency, we test setting an assortment of scales including 50, 100, 200, 400, 800 for the word references. We report the outcomes on the Subway dataset in Table IV. With programmed word reference scale estimation, our strategy runs speedier and yields more exact recognition result. We likewise think about results on the UCSD Ped1 Dataset. We tune the limit (number of uncommon subregion) to plot the ROC bend, given in Fig. 3. These trials recommend that scale adjustment for word reference learning is essential. On the off chance that the appointed scale is lower than should be expected, ordinary examples may not be decently spoken to, bringing about high false caution. On other hand, an excessively expansive lexicon might easily speak to anomalous examples, expanding vagueness. Note that hand-tuning these scales for all districts are incomprehensible.

Table IV: result comparison on the subway entrance video. “gt” stands For ground truth. “PDS” means all sub-regions have the same Dictionary scale. Events include wd (wrong direction), NP (no payment), LT (loitering), II (irregular interactions), All (sum of all unusual cases), and FA (false alarm).

	WD	NP	LT	II	misc	All	fa
GT	25	12	14	4	9	64	0
PDS = 50	21	13	12	4	7	57	25
PDS = 100	20	7	13	4	7	51	19
PDS = 200	22	8	11	4	7	52	12
PDS = 400	20	9	11	4	8	52	6
PDS = 800	19	8	10	4	7	48	5
Ours	22	9	12	4	8	55	5

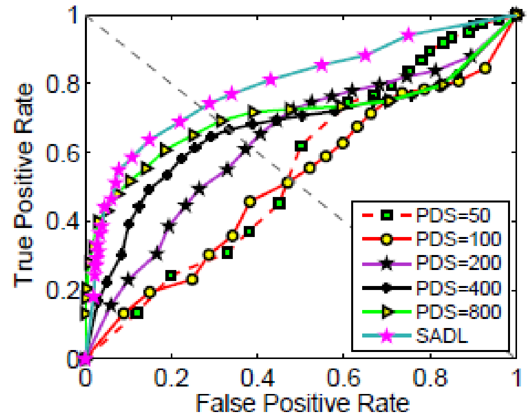

Figure 3: ROC curve on the UCSD Ped1 Dataset [15].

These examinations propose that scale adjustment for word reference learning is imperative. On the off chance that the relegated scale is lower than should be expected, ordinary examples may not be decently spoken to, bringing about high false alert. On other hand, an excessively vast lexicon might easily speak to strange examples, expanding uncertainty. Note that hand-tuning this scale for all locales is inconceivable.

CONCLUSION

We have displayed another model to consequently appraise word reference size amid learning. It includes Atom Indicator Vectors (AIVs) to show if one premise is vital or not by assessing the reactions. The last capacity is unraveled by approximating the novel measurement compelling term by a Multivariate Moreau Proximal Indicator (MMPI) punishment. We assess the viability of our framework utilizing surface and human activity illustrations. They show that our evaluated word reference scale is suitable. Our structure is general. It could perhaps profit numerous picture transforming and PC vision issues and helps spare time and exertion in discovering rectify the scales.

REFERENCES:

1. E. Michael and A. Micha, “K-svd: an algorithm for designing overcomplete dictionaries for sparse representation,” IEEE Transactions on Image Processing (TIP), vol. 54, no. 11, pp. 4311–4322, 2006.
2. G. Peyr´e, “Sparse modeling of textures,” Journal of Mathematical Imaging and Vision, vol. 34, no. 1, pp. 17–31, 2009.
3. T. Ivana and F. Pascal, “Dictionary learning for stereo image representation,” IEEE Transactions on Image Processing (TIP), vol. 20, no. 4, pp. 921–934, 2011.
4. E. Michael and A. Michal, “Image denoising via sparse and redundant representations over learned dictionaries,” IEEE Transactions on Image Processing (TIP), vol. 15, no. 12, pp. 3736–3745, 2006.
5. J. Shi, X. Ren, G. Dai, J. Wang, and Z. Zhang, “A non-convex relaxation approach to sparse dictionary learning,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2011, pp. 1809–1816.
6. Y. Jianchao, W. John, H. Thomas, and Y. Ma, “Image super-resolution via sparse representation,” IEEE Transactions on Image Processing (TIP), vol. 19, no. 11, pp. 2861–2873, 2010.
7. C. Lu, J. Shi, and J. Jia, “Abnormal event detection at 150 fps in matlab,” in International Conference on Computer Vision (ICCV), 2013.
8. C. Lu, J. Shi, and J. Jia, “Online robust dictionary learning,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2013.
9. M. Julien, B. Francis, PonceJean, and S. Guillermo, “Online learning for matrix factorization and sparse coding,” The Journal of Machine Learning Research, vol. 11, pp. 19–60, 2010.
10. M. Zhou, H. Chen, P. John, L. Ren, S. Guillermo, and C. Lawrence, “Non-parametric bayesian dictionary learning for sparse image representations,” Advances in Neural Information Processing Systems (NIPS), 2009.
11. I. Ramirez and G. Sapiro, “An mdl framework for sparse coding and dictionary learning,” IEEE Transactions on Signal Processing, vol. 60, no. 6, pp. 2913–2927, 2012.
12. M. Yang, L. Zhang, X. Feng, and D. Zhang, “Fisher discrimination dictionary learning for sparse representation,” in International Conference on Computer Vision (ICCV), 2011, pp. 543–550.
13. C. Antonio, P. Patrick, and T. Kentaro, “Region filling and object removal by exemplar-based image inpainting,” IEEE Transactions on Image Processing (TIP), vol. 13, no. 9, pp. 1200–1212, 2004.
14. P. Nikos and D. Rachid, “Geodesic active regions and level set methods for supervised texture segmentation,” International Journal on Computer Vision (IJCV), vol. 46, no. 3, pp. 223–247, 2002
15. R. Mehran, A. Oyama, and M. Shah, “Abnormal crowd behavior detection using social force model,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2009, pp. 935–942.