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TITLE, AUTHOR, PUBLICATION YEAR IEEE SPS PUBLICATIONS	ABSTRACT	RANK IN IEEE TOP 100						*N* TIMES IN TOP 100 (SINCE JAN 2011)
		MAR 2014	FEB 2014	JAN 2014	DEC 2013	NOV 2013	OCT 2013	
A TUTORIAL ON PARTICLE FILTERS FOR ONLINE NONLINEAR/NON-GAUSSIAN-BAYESIAN TRACKING Arulampalam, M.S.; Maskell,S.; Gordon, N.; Clapp, T. *IEEE Transactions on Signal Processing* vol. 50, no. 2, 2002, pp. 174–188	This paper reviews optimal and suboptimal Bayesian algorithms for nonlinear/non-Gaussian tracking problems, with a focus on particle filters. Variants of the particle filter are introduced within a framework of the sequential importance sampling algorithm and compared with the standard EKF.	9	10	31	8	**6**	25	36
AN INTRODUCTION TO COMPRESSIVE SAMPLING Candes, E.J.; Wakin, M.B. *IEEE Signal Processing Magazine* vol. 25, no. 2, Mar. 2008, pp. 21–30	This article surveys the theory of compressive sampling, also known as compressed sensing or CS, a novel sensing/sampling paradigm that goes against the common wisdom in data acquisition.	21	19	14	**10**	11	**10**	38
IMAGE QUALITY ASSESSMENT: FROM ERROR VISIBILITY TO STRUCTURAL SIMILARITY Zhou W.; Bovik, A.C.; Sheikh, H.R.; Simoncelli, E.P. *IEEE Transactions on Image Processing* vol. 13, no. 4, 2004, pp. 600–612	This paper introduces a framework for quality assessment based on the degradation of structural information. Within this framework a structure similarity index is developed and evaluated. MATLAB code available.	31	42	**24**	28	24	33	18
VECTOR-VALUED IMAGE PROCESSING BY PARALLEL LEVEL SETS Ehrhardt, M.J.; Arridge, S.R. *IEEE Transactions on Image Processing* vol. 23, no. 1, pp 8–9	This paper considers the components of an image as a vector. By minimizing large angles parallel level sets are obtained and used for demosaicking.	50	58	**22**	98			4
IMAGE SUPER-RESOLUTION VIA SPARSE REPRESENTATION Yang, J.; Wright, J.; Huang, T.S.; Ma, Y. *IEEE Transactions on Image Processing* vol. 19, no. 11, 2010, pp. 2861–2873	This paper presents an approach to single-image super-resolution, based upon sparse signal representation of low and high-resolution patches.	55	92	**27**	31	44	51	10

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		MAR 2014	FEB 2014	JAN 2014	DEC 2013	NOV 2013	OCT 2013	
SCALING UP MIMO: OPPORTUNITIES AND CHALLENGES WITH VERY LARGE ARRAYS Rusek, F.; Persson, D.; Lau, B.K.; Larsson, E.G.; Marzetta, T.L.; Edfors, O.; Tufvesson, F. *IEEE Signal Processing Magazine* vol. 30, no. 1, 2013, pp. 40–60	The more antennas the transmitter/receiver is equipped with, and the more degrees of freedom that the propagation channel can provide, the better the performance in terms of data rate or link reliability. This article quantifies the reliability and achievable rates.	78		82	**43**	75		12
K-SVD: AN ALGORITHM FOR DESIGNING OVERCOMPLETE DICTIONARIES FOR SPARSE REPRESENTATION Aharon, M.; Elad, M.; Bruckstein, A. *IEEE Transactions on Signal Processing* vol. 54, no. 11, 2006, pp. 4311–4322	K-SVD is an iterative method that alternates between sparse coding of the training examples based on the current dictionary and a process of updating the dictionary atoms to better fit the data and can be used with any pursuit method.	**87**						1
IMAGE QUALITY ASSESSMENT FOR FAKE BIOMETRIC DETECTION: APPLICATION TO IRIS, FINGERPRINT, AND FACE RECOGNITION Galbally, J.; Marcel, S; Fierrez, J. *IEEE Transactions on Image Processing* vol. 23, no. 2, 2014, pp. 710–724	This paper uses 25 general image-quality features extracted from the authentication image to distinguish between legitimate and imposter samples for fingerprint, iris, and two-dimensional face biometrics.		74	**50**				2
SUPER-RESOLUTION IMAGE RECONSTRUCTION: A TECHNICAL OVERVIEW Cheol Park, S; Kyu Park, M.; Gi Kang, M. *IEEE Signal Processing Magazine* vol. 20, no. 3, 2003, pp. 21–36	This article introduces the concept of super-resolutions (SR) algorithms and presents a technical review of various existing SR methodologies and models the low-resolution image acquisition process.			43	**34**	45	90	4
IMAGE PROCESSING USING SMOOTH ORDERING OF ITS PATCHES Ram, I.; Elad, M.; Cohen, I. *IEEE Transactions on Image Processing* vol. 22, no. 7, 2013, pp. 2764–2774	This paper extracts overlapping image patches, orders these patches, and applies one-dimensional filtering to the reordered set of pixels. These techniques are applied to denoising and inpainting.			60	63	90	**36**	8
FINGERPRINT COMPRESSION BASED ON SPARSE REPRESENTATION Guangqui, S; Wu, Y; Yong, A., Liu, X.; Guo, T. *IEEE Transactions on Image Processing* vol. 23, no. 2, 2014, pp. 489–501	Compression using a sparse linear combination of dictionary atoms are used to compress three groups of finger print images and compared with JPEG, JPEG2000, and WSQ.			**66**				1
GLOBAL IMAGE DENOISING Talebi, H.; Milanfar, P. *IEEE Transactions on Image Processing* vol. 23, no. 2, 2014, pp. 755–768	This paper improves on patch similarity denoising methods by using spectral components from all pixels in an image. This global filter can be approximated by sampling a small percentage of pixels in the image.			**67**				1
COMPRESSIVE SENSING [LECTURE NOTES] Baraniuk, R.G. *IEEE Signal Processing Magazine* vol. 24, no. 4, 2007, pp. 118–121	This lecture note presents a new method to capture and represent compressible signals at a rate significantly below the Nyquist rate. This method, called compressive sensing, employs nonadaptive linear projections that preserve the structure of the signal; the signal is then reconstructed from these projections using an optimization process.			73	**39**	58	60	10

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