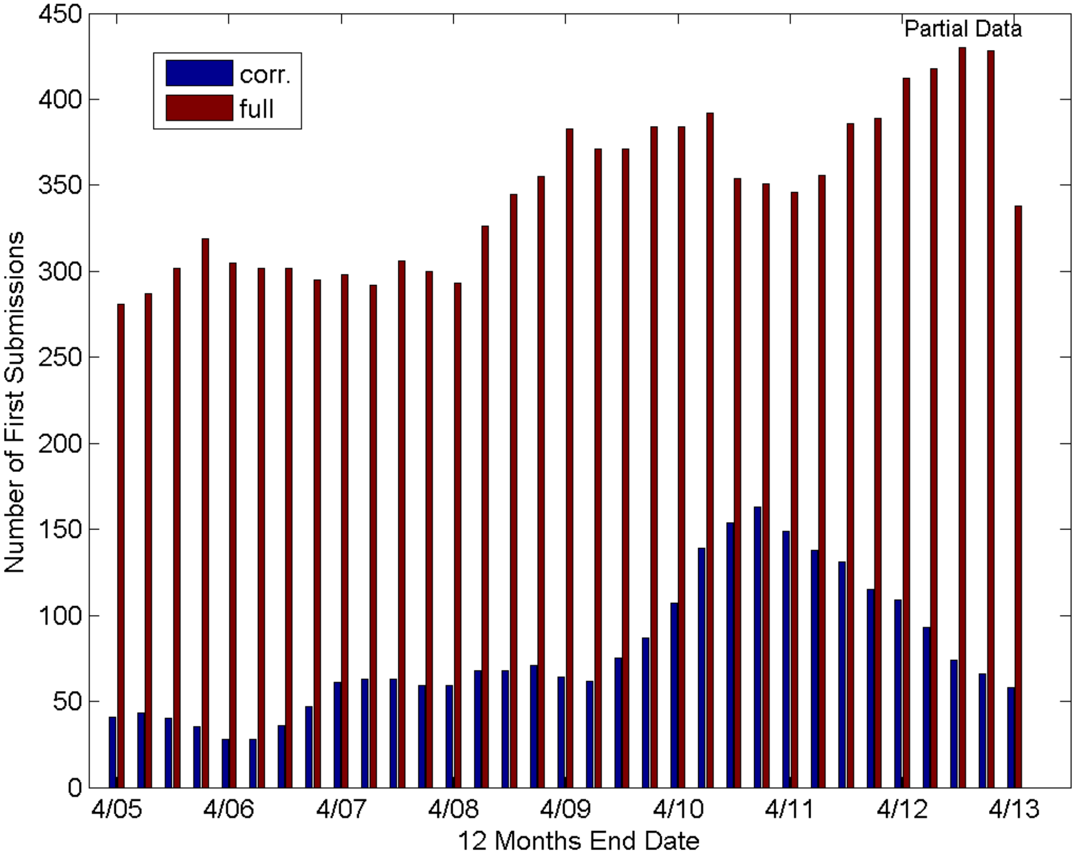
Status of the IEEE Transactions on Aerospace and Electronic Systems

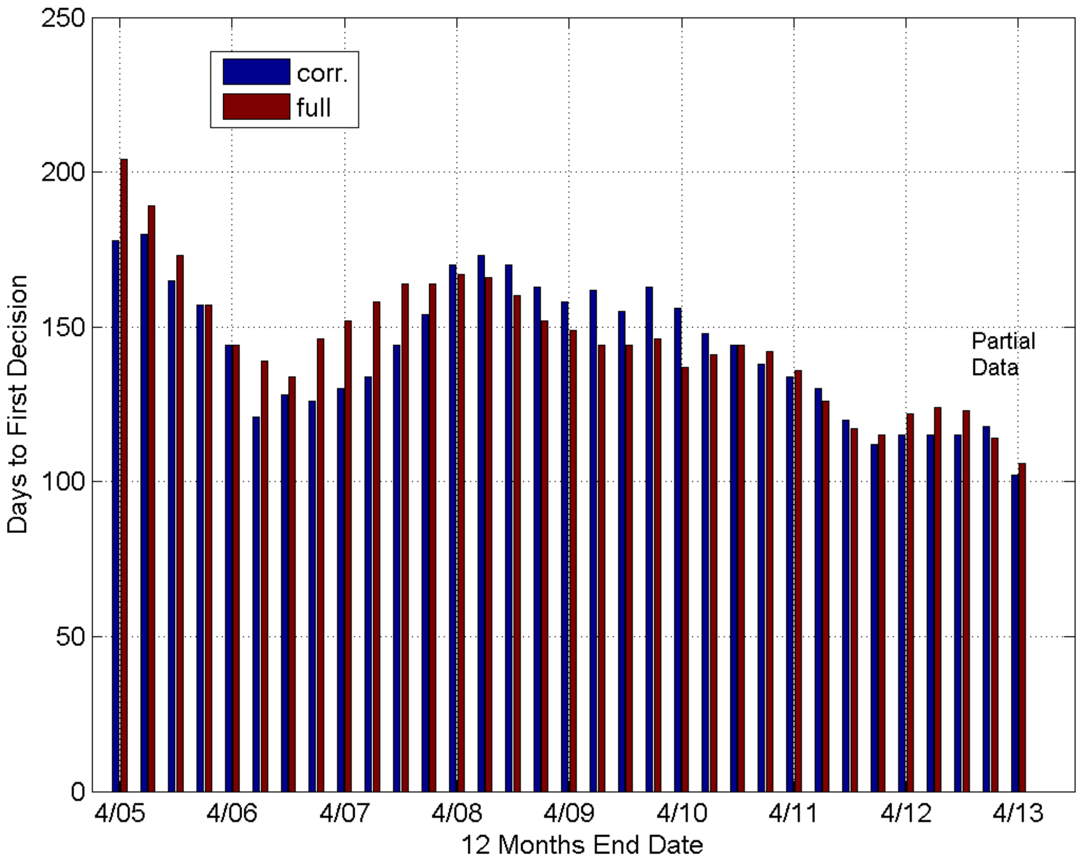
Lance Kaplan, Editor-In-Chief

May 3rd, 2013

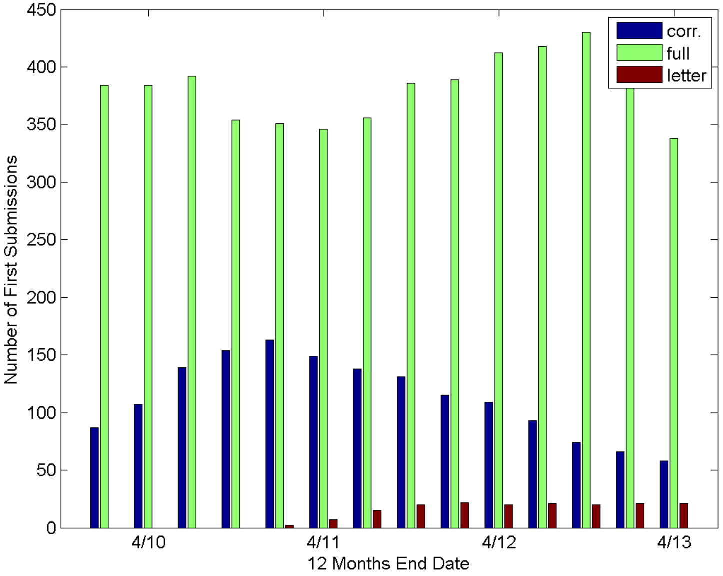
Number of Submissions



Time to First Decisions



Letters



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450
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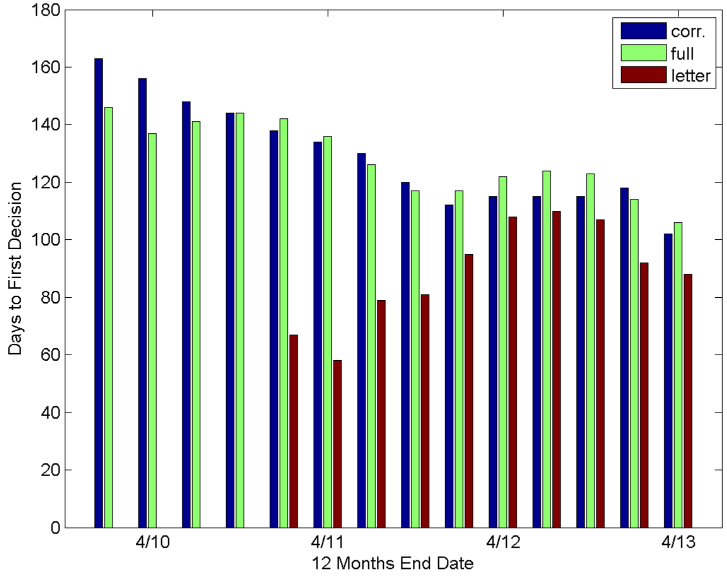
Number of First Submissions
4/10
4/11
4/12
4/13
12 Months End Date



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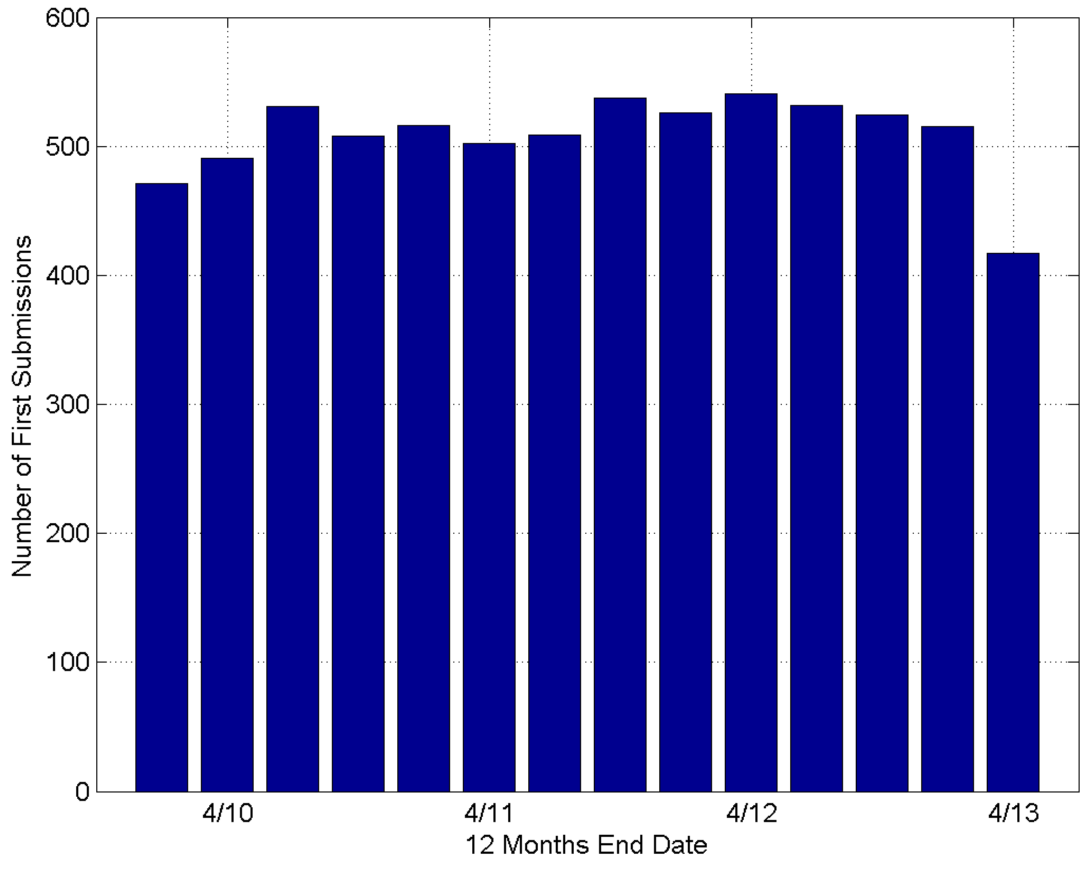
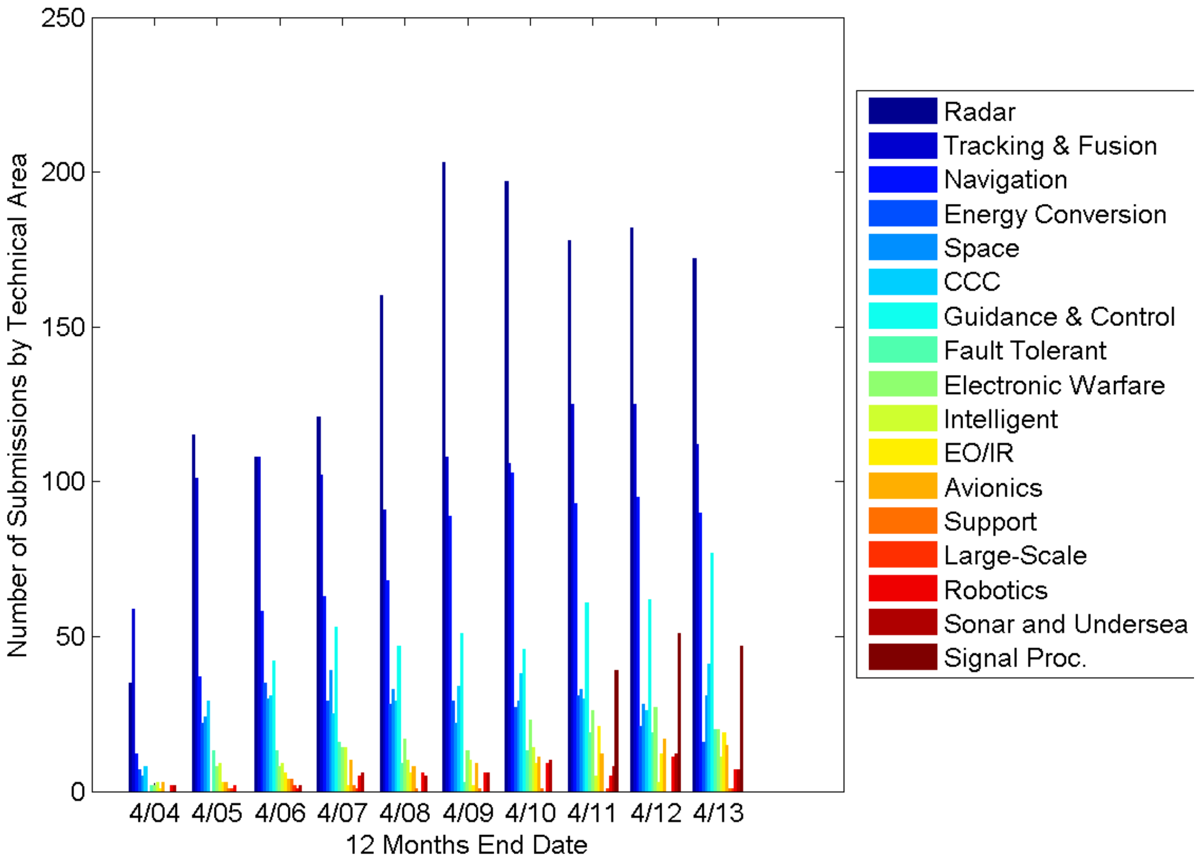
Days to First Decision
4/10
4/11
4/12
4/13
12 Months End Date

Total Submissions



Submissions by Technical Area



IEEE Policy News

- Open Access
  - IEEE Access
  - Hybrid Model
  - White House Directive
- IEEE Xplore
  - HTML and PDF will be available
  - New XML Metadata requirements
  - Early posting of preprints
- CrossCheck
  - IEEE checks after acceptance
  - We can check at submission
- Publication of Conference Papers
  - Each journal has its own policy
  - We require authors to expand their papers

Other Issues

- Page Overlength Charges
  - Encourage succinct papers
  - Allows us to accommodate more papers
  - IEEE collects the money
  - We need to know who does not pay
- Paper Format
  - TAES does have a distinct look
  - But current format waste space
  - And many do not like ragged right
- 2010 Barry Carlton Award
  - Paper has been selected
  - Need to collect letters of endorsement

Paper Format

I. INTRODUCTION

A Multiple IMM Estimation Approach with Unbiased Mixing for Thrusting Projectiles

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YAAKOV BAR-SHALOM, Fellow, IEEE
PETER WILLETT, Fellow, IEEE
E. MOZESON
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University of Connecticut

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AMRDEC

We present a procedure to estimate the state of thrusting/ballistic endoatmospheric projectiles for the end purpose of impact point prediction. The short observation time and the estimation ambiguity between drag and thrust in the dynamic model motivate the development of a multiple interacting multiple model (MIMM) estimator with various drag coefficient initializations. A simple unbiased IMM mixing procedure (useful for quite general applications) is presented for state estimators with unequal dimensions and applied for the thrusting and ballistic modes in the case considered. Results with real data are given.

Manuscript received September 14, 2011; released for publication December 12, 2011.

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Refereeing of this contribution was handled by L. Kaplan.

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Authors' addresses: T. Yuan, Y. Bar-Shalom, P. Willett, E. Mozeson, and S. Pollak, Department of Electrical and Computer Engineering, University of Connecticut, 371 Fairfield Rd., Storrs, CT 06269-9005, E-mail: (p.willett@ieee.org); D. Hardiman, U.S. Army Aviation and Missile Research, Development, and Engineering Center (AMRDEC).

The trajectory of a thrusting projectile can be divided into two phases: thrusting and ballistic. The target dynamics are substantially different and characterized by different main forces in each phase. The resulting acceleration can be written in terms of the thrust, drag, and gravity components [3] (the lift force is neglected in this work, since it is very small in the scenarios considered) as

$$\mathbf{a}_F = \mathbf{a}_T + \mathbf{a}_D + \mathbf{a}_G. \tag{1}$$

For the thrusting phase, we consider thrust, drag, and gravity; for the ballistic phase, only gravity and drag. For a trajectory with unknown drag coefficient and unknown thrust, it is difficult to clearly divide the trajectory into its phases. The interacting multiple model (IMM) estimator with a thrust mode (TM) and a ballistic mode (BM) to match these two phases is a natural choice (it is assumed that no optical indication of the plume is available, as in the real-data examples considered).

Given a very short observation period of a thrusting/ballistic projectile for the purpose of impact point prediction (IPP), an accurate estimate of the target state (including its thrust and drag coefficient) is of the utmost importance. The IPP accuracy depends mainly on the drag coefficient estimate since the prediction is done after the thrusting period is over, i.e., based on the BM. Note that the net acceleration (1) includes the (algebraic) sum of the drag and thrust, thus causing an ambiguity in the estimation when both are unknown. A better initial estimate of the drag coefficient is conducive to a more accurate estimate of the thrust, which then results in a more accurate overall state estimate and better IPP performance. The sensitivity of the system performance to the drag coefficient estimate leads to using a multiple IMM (MIMM) estimator to overcome the above-mentioned ambiguity to more accurately estimate the drag coefficient and thrust. The technique involves evaluating the likelihood functions of the IMM estimators with different initial drag coefficient estimates to quantify how well the MIMM estimators fit the observation data [6].

Another issue that arises is the mixing of the mode-conditioned state estimates in an IMM estimator when the modes used have different dimension state vectors. The conventional approach in this case is to augment with zeros the lower dimension state estimate prior to the mixing [2]. However, this leads to a bias toward zero for the state components of the larger state vector that are mixed with the extra components of the smaller state that are zero. A simple procedure to avoid this "biasing" is presented, together with a suitable augmentation of the covariance of the smaller state that yields an unbiased and consistent mixing. This leads to a "direct" block mixing in contrast to

The MIMO Radar and Jammer Games

Xiufeng Song, *Student Member, IEEE*, Peter Willett, *Fellow, IEEE*, Shengli Zhou, *Senior Member, IEEE*, and Peter B. Luh, *Fellow, IEEE*

***Abstract*—The interaction between a smart target and a smart MIMO radar is investigated from a game theory perspective. Since the target and the radar form an adversarial system, their interaction is modeled as a two-person zero-sum game. The mutual information criterion is used in formulating the utility functions. The unilateral, hierarchical, and symmetric games are studied, and the equilibria solutions are derived.**

***Index Terms*—Game theory, hierarchical game, jamming, MIMO radar, Nash equilibrium, Stackelberg equilibrium, waveform.**

I. INTRODUCTION

THE success of the multiple-input multiple-output (MIMO) structure in communications has inspired investigation of MIMO radar. MIMO radars do not have a standard definition, and current literature divides them into statistical [1] and co-located [2], based on the antenna configuration. Generally, a statistical MIMO radar leverages the diversity of propagation path with sufficiently dissimilar transmitter-receiver geometry to improve detection, estimation, and information extraction [1], [3]–[8]; while a co-located one implies spatially coherent processing such as beamforming and direction-of-arrival estimation [2], [9]–[11]. The eventual acceptance of MIMO radar still remains unclear [12].

Waveform diversity is a key feature of a MIMO radar system [2]–[16]. It emphasizes illumination cooperation, and may provide an opportunity to upgrade radar performance. The specification of a waveform set largely depends on the system task. For propagation path separation, waveforms are required to be (near) orthogonal in order to avoid cross interference [3], [13]–[15]. In beampattern design, waveforms are correlated, so maximal transmission power can be focused in a certain direction [9]–[11]. In information extraction, the mutual information (MI) between the target response and collected echoes is maximized [4]–[8]. In target detection, optimized waveforms are designed to assure least likely missed detection

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Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TSP.2011.2169251

for a given false alarm rate [8] or to maximize the signal-to-interference-plus-noise ratio [16]. And in target scatterer matrix estimation, waveforms are optimized for minimum mean square error [4]–[6].

Among those waveform design criteria, MI has acquired extensive attention. In the pioneering work [17], Woodward first suggested the application of information theory to radar receiver design. Later, Bell showed that maximizing the MI between target impulse response and measurement may enable the radar system a better capacity in characterizing the target in a contaminated environment [18]. Some interesting extensions including MI based waveform design in the presence of multiple targets [19], MI based MIMO radar space time code optimization [8] and waveform design [4]–[7] emerge thereafter. In this paper, we will concentrate on the application of the MI criterion to statistical MIMO radar.

Current literature on MIMO radar waveform design prefers to investigate the interaction between a *smart* radar and a *dumb* target, where the former has some knowledge of the latter such as radar cross section (RCS) distribution, while the latter is incapable of interfering with the former. Actually, with the development of electronic warfare, many noncooperative targets such as fighters are equipped with countermeasure systems to prevent a radar from operating as well as it might [20]. In this paper, the interaction involves a smart target, which carries jamming equipment that could intelligently confuse the radar. If the target always tries to prevent a radar from fulfilling its task, the interaction between them can be modeled as a two-person zero-sum (TPZS) game [21].

As in [4]–[8], the MI criterion is utilized to formulate the utility functions. The radar controls the waveform matrix to maximize the MI, while the latter has some access to its jamming matrix to minimize it. The contributions of this paper are as follows.

- We suggest the use of a MI based TPZS game to model the interaction between a target and MIMO radar, and categorize the game into one of three—unilateral, hierarchial, and symmetric—based on the information set available for each player.
- In the unilateral case, where one player can intercept the other's strategy while the latter *does not* notice that this is happening, the TPZS games are simplified as single person optimizations. For this case, the optimal (water-filling) strategies are derived.
- In the hierarchial case, where one player can intercept the other's strategy while the latter *does* notice that, the TPZS game is recast as a conservative minmax or maxmin two-stage optimization. The Stackelberg equilibria—optimization solutions—are derived.

Paper Format II

I. INTRODUCTION

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Convex and Semi-Nonnegative Matrix Factorizations

Chris Ding, *Member, IEEE*, Tao Li, and Michael I. Jordan, *Fellow, IEEE*

Abstract—We present several new variations on the theme of nonnegative matrix factorization (NMF). Considering factorizations of the form $X = FG^T$, we focus on algorithms in which G is restricted to containing nonnegative entries, but allowing the data matrix X to have mixed signs, thus extending the applicable range of NMF methods. We also consider algorithms in which the basis vectors of F are constrained to be convex combinations of the data points. This is used for a kernel extension of NMF. We provide algorithms for computing these new factorizations and we provide supporting theoretical analysis. We also analyze the relationships between our algorithms and clustering algorithms, and consider the implications for sparseness of solutions. Finally, we present experimental results that explore the properties of these new methods.

Index Terms—Nonnegative matrix factorization, singular value decomposition, clustering.

1 INTRODUCTION

Matrix factorization is a unifying theme in numerical linear algebra. A wide variety of matrix factorization algorithms have been developed over many decades, providing a numerical platform for matrix operations such as solving linear systems, spectral decomposition, and subspace identification. Some of these algorithms have also proven useful in statistical data analysis, most notably the singular value decomposition (SVD), which underlies principal component analysis (PCA).

Recent work in machine learning has focused on matrix factorizations that directly target some of the special features of statistical data analysis. In particular, nonnegative matrix factorization (NMF) [1], [2] focuses on the analysis of data matrices whose elements are nonnegative, a common occurrence in data sets derived from text and images. Moreover, NMF yields nonnegative factors, which can be advantageous from the point of view of interpretability.

The scope of research on NMF has grown rapidly in recent years. NMF has been shown to be useful in a variety of applied settings, including environmetrics [3], chemometrics [4], pattern recognition [5], multimedia data analysis [6], text mining [7], [8], DNA gene expression analysis [9], [10], and protein interaction [11]. Algorithmic extensions of NMF have been developed to accommodate a variety of objective functions [12], [13] and a variety of data analysis problems, including classification [14] and collaborative filtering [15]. A number of studies have focused on further developing computational methodologies for NMF [16], [17], [18], [19]. Finally, researchers have begun to explore some of the relationships between matrix factorizations and K-means clustering [20], making use of the least square objectives of NMF; as we emphasize in the current paper, this relationship has implications for the interpretability of matrix factors. NMF with the Kullback-Leibler (KL) divergence objective has been shown [21], [13] to be equivalent to probabilistic latent semantic analysis [22], which has been further developed into the fully probabilistic latent Dirichlet allocation model [23], [24].

Our goal in this paper is to expand the repertoire of nonnegative matrix factorization. Our focus is on algorithms that constrain the matrix factors; we do not require the data matrix to be similarly constrained. In particular, we develop NMF-like algorithms that yield nonnegative factors but do not require the data matrix to be nonnegative. This extends the range of application of NMF ideas. Moreover, by focusing on constraints on the matrix factors, we are able to strengthen the connections between NMF and K-means clustering. Note in particular that the result of a K-means clustering run can be written as a matrix factorization $X = FG^T$, where X is the data matrix, F contains the cluster centroids, and G contains the cluster membership indicators. Although F typically has entries with both positive and negative signs, G is nonnegative. This motivates us to propose general factorizations in which G is restricted to be nonnegative and F is unconstrained. We also consider algorithms that constrain F; in particular, restricting the columns of F to be convex combinations of data points in X we obtain a matrix factorization that can be interpreted in terms of weighted cluster centroids.

The paper is organized as follows: In Section 2, we present the new matrix factorizations, and in Section 3, we present algorithms for computing these factorizations. Section 4 provides a theoretical analysis, which provides insights into the sparseness of matrix factors for a convex variant of NMF. In Section 5, we consider extensions of Convex-NMF and the relationships of NMF-like factorizations. In Section 5.1, we show that a convex variant of NMF has the advantage that it is

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Digital Object Identifier no. 10.1109/TPAMI.2008.277.

Published by the IEEE Computer Society

Special Section:
CS Applied to Radar

- 31 papers submitted
- 2 accepted
- 12 rejected
- 10 still under process
- Target date for final manuscripts was April 2013
- Expect the process for the remaining 10 papers to be completed in 6 months.

Editors

- Resignations
  - Fredrik Gustafsson (Tracking & Multisensor Systems)
  - Ulrich Nickel (Radar Systems)
  - Salah Sukkarieh (Robotics Systems)
- New Appointees
  - Joseph Homer Saleh (Space Systems)
  - Luis Rodrigues (Guidance and Control Systems)
  - Kegen Yu (Navigation)
  - Junfeng Li (Guidance and Control Systems)
- To be added:
  - Geoffrey San Antonio (Radar Systems)
  - Giuseppe Fabrizio (Radar Systems)
  - Michael Inggs (Radar Systems)

AE Performance

	Time to first report (days)			Final disposition of papers reaching first report						
Name	Average	Max	Min	Accepted	Rejected	Decision to	Withdrawn	No Decisio	Total	Acceptance Rate (%)
Abramovich, Yuri	359	557	162	1	0	0	0	1	2	100
Adve, Raviraj	112	191	58	1	1	10	0	3	5	50
Akella, Maruthi R.	468	468	468	1	0	0	0	3	4	100
Aloi, Daniel	69	158	0	2	8	1	0	4	14	20
Baker, Chris	143	420	63	5	5	7	0	6	16	50
Bell, Mark	399	399	399	1	0	0	0	0	1	100
Blair, William	0	0	0	0	0	0	0	0	0	0
Blanding, Wayne	108	173	0	6	11	10	0	4	21	35
Blanke, Mogens	188	322	0	1	2	2	0	6	9	33
Blunt, Shannon	94	132	1	3	3	7	0	2	8	50
Braasch, Michael	122	170	69	9	0	4	0	0	9	100
Campbell, Mark E.	0	0	0	0	0	0	0	0	0	0
Choukroun, Daniel	238	307	182	0	1	1	0	4	5	0
Coraluppi, Stefano	104	139	81	4	3	3	0	5	12	57
Dempster, Andrew	109	180	73	3	2	13	0	2	7	60
Efe, Murat	104	316	0	5	9	6	0	2	16	36
Ender, Joachim	140	147	134	0	2	2	0	1	3	0
Gebre-Egziabher, De	0	0	0	0	0	0	0	0	0	0
Ghose, Debasish	123	184	78	3	4	4	0	4	11	43
Gini, Fulvio	78	141	1	4	6	15	0	1	11	40
Goodman, Nathan	127	220	25	0	1	4	0	8	9	0
Groves, Paul	130	279	9	1	8	1	0	4	13	11
Gustafsson, Fredrik	184	243	124	2	2	0	0	3	7	50
Hablani, Hari	0	0	0	0	0	0	0	0	0	0
Hanebeck, Uwe	108	270	0	1	15	0	0	9	25	6
Hary, Stephen	125	258	20	4	8	4	0	3	15	33
Hwang, Inseok	122	162	73	2	2	3	0	5	9	50
Idan, Moshe	100	181	3	1	6	4	0	5	12	14
Jah, Moriba	102	109	94	1	2	6	0	1	4	33
Jauffret, Claude	158	235	95	2	0	1	0	3	5	100
Kaplan, Lance	33	157	0	7	32	20	0	4	43	18
Khorasani, K.	134	171	65	0	1	0	0	3	4	0
Koch, Wolfgang	117	339	0	8	12	15	0	8	28	40
Krishnamurthy, Vikra	0	0	0	0	0	0	0	0	0	0
Kwon, Heesung	82	189	1	3	4	12	0	6	13	43

AE Performance (Cont)

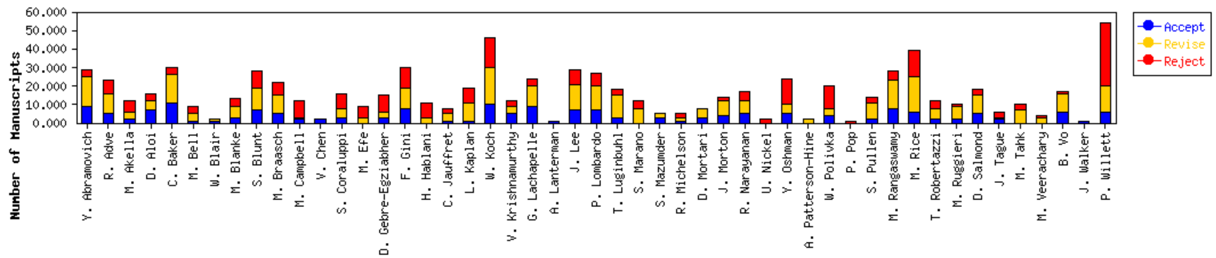
	Time to first report (days)			Final disposition of papers reaching first report							
Name	Average	Max	Min	Accepted	Rejected	Decision to	Withdrawn	No Decisio	Total	Acceptance Rate (%)	
Lachapelle, Gerard	0	0	0	0	0	0	0	0	0	0	
Lee, Jim	0	0	0	0	0	0	0	0	0	0	
Li, Junfeng	120	128	109	0	1	2	0	2	3	0	
Lombardo, Pierfranc	219	287	127	2	1	11	0	4	7	67	
Luginbuhl, Tod	282	314	246	3	1	1	0	5	9	75	
Marano, Stefano	98	143	19	5	8	8	0	8	21	38	
Mazumder, Sudip	475	628	249	0	0	0	0	1	1	0	
Michelson, Robert	0	0	0	1	0	0	0	0	1	100	
Mihaylova, Lyudmila	151	331	74	0	0	7	0	4	4	0	
Mortari, Daniele	0	0	0	0	0	0	0	2	2	0	
Morton, Jade	98	187	1	2	5	1	0	3	10	29	
Nakasuka, Shinichi	154	184	135	0	0	4	1	3	4	0	
Narayanan, Ram	80	112	5	7	1	10	0	5	13	88	
Nickel, Ulrich	108	222	59	8	3	17	0	5	16	73	
Patterson-Hine, Ann	0	0	0	0	0	0	0	0	0	0	
Polivka, William	61	175	0	1	7	3	0	0	8	13	
Pullen, Sam	322	322	322	0	0	1	0	0	0	0	
Rangaswamy, Mural	261	1083	0	2	3	3	0	0	5	40	
Rauhut, Holger	84	93	72	0	0	5	0	0	0	0	
Rice, Michael	78	201	0	7	8	12	0	7	22	47	
Robertazzi, Thomas	126	212	0	3	2	4	0	5	10	60	
Rodrigues, Luis	0	0	0	0	0	0	0	0	0	0	
Ruggieri, Marina	0	0	0	0	0	0	0	0	0	0	
Saleh, Joseph	0	0	0	0	0	0	0	0	0	0	
Salmond, David	0	0	0	0	0	0	0	0	0	0	
Schirinzi, Gilda	90	94	84	0	2	2	0	0	2	0	
Strohmer, Thomas	189	224	148	0	2	1	0	1	3	0	
Sukkarieh, Salah	80	155	0	0	5	4	0	1	6	0	
Tague, John	76	194	0	5	1	0	0	0	6	83	
Tahk, Min-Jea	110	226	0	0	1	6	0	2	3	0	
Veerachary, Mumma	175	249	102	2	0	1	0	0	2	100	
Vladimirova, Tanya	209	312	161	1	0	4	0	0	1	100	
Vo, Ba-Ngu	120	245	4	3	3	4	0	3	9	50	
Watts, Simon	114	312	62	3	6	4	0	2	11	33	
Weiss, Matthias	121	151	35	0	1	4	0	1	2	0	

AE Performance (Cont)

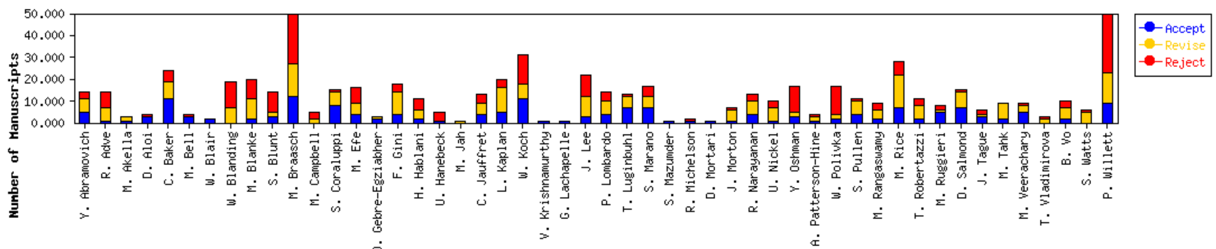
	Time to first report (days)			Final disposition of papers reaching first report							
Name	Average	Max	Min	Accepted	Rejected	Decision to	Withdrawn	No Decisio	Total	Acceptance Rate (%)	
Willett, Peter	159	327	61	7	3	4	0	0	10	70	
Wong, Kainam Thon	89	165	0	1	7	5	0	2	10	13	
Yu, Kegen	0	0	0	0	0	0	0	5	5	0	

AE Report Card

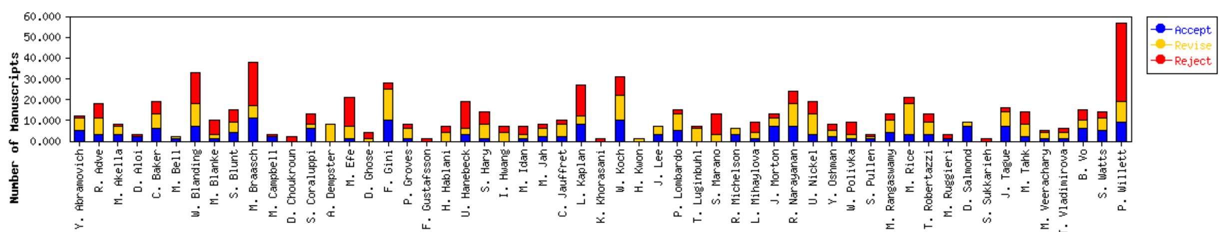
Dates: 4/1/2009 to 3/31/2010



Dates: 4/1/2010 to 3/31/2011



Dates: 4/1/2011 to 3/31/2012



Dates: 4/1/2012 to 3/31/2013