PATENT ASSIGNMENT

Electronic Version v1.1
Stylesheet Version v1.1

SUBMISSION TYPE:	NEW ASSIGNMENT
NATURE OF CONVEYANCE:	ASSIGNMENT

CONVEYING PARTY DATA

Name	Execution Date
The Penn State Research Foundation	02/06/2013

RECEIVING PARTY DATA

Name:	Xerox Corporation
Street Address:	45 Glover Avenue
Internal Address:	P.O. Box 4505
City:	Norwalk
State/Country:	CONNECTICUT
Postal Code:	06856-4505

PROPERTY NUMBERS Total: 1

Property Type	Number
Application Number:	13773097

CORRESPONDENCE DATA

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ATTORNEY DOCKET NUMBER:	20121050-US-NP
NAME OF SUBMITTER:	Kermit Lopez

Total Attachments: 19
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INTELLECTUAL PROPERTY RIGHTS ASSIGNMENT AGREEMENT

This Intellectual Property Rights Assignment Agreement (this "Assignment Agreement"), effective upon the date of last signature (the "Effective Date"), is by and between The Penn State Research Foundation ("PSRF"), a non-profit corporation duly organized and existing under the laws of the Commonwealth of Pennsylvania and having an office at 304 Old Main, University Park, PA 16802, and Xerox Corporation, a corporation organized under the laws of the state of New York ("ASSIGNEE"), having its principal office at 45 Glover Avenue, Norwalk, CT 06856.

WITNESSETH

WHEREAS, ASSIGNEE and The Pennsylvania State University ("UNIVERSITY") entered into a Sponsored Research Agreement effective on July 20, 2012 (No. 145376);

WHEREAS, Vishal Monga and Xuan Mo, employees of the UNIVERSITY ("UNIVERSITY INVENTORS") have made a joint invention with ASSIGNEE titled "Anomaly Detection Using a Kernel-Based Sparse Reconstruction Model", filed as The Pennsylvania State University Invention Disclosure No. 2012-3983, and in U.S. Provisional Patent Application Serial No. 61/731,133 filed on November 29, 2012, and any non-provisional, continuations and divisionals thereof, U.S. and/or foreign ("INVENTION");

WHEREAS, under the terms of the Sponsored Research Agreement effective on July 20, 2012 (No. 145376), ASSIGNEE is to receive ownership of all joint intellectual property ("Joint IP") created during performance of the sponsored research project by UNIVERSITY;

WHEREAS, PSRF is a wholly owned subsidiary of UNIVERSITY and is UNIVERSITY's designee to manage UNIVERSITY's intellectual property;

WHEREAS, pursuant to the terms of the UNIVERSITY's Intellectual Property Agreement, the UNIVERSITY INVENTORS, have assigned their entire right title and interest in the Joint IP including INVENTION to PSRF;

WHEREAS, upon full execution of this Assignment Agreement PSRF hereby assigns ownership of the Joint IP to ASSIGNEE;

NOW THEREFORE, in consideration of the premises and the mutual promises and covenants set forth below, and for other good and valuable consideration, the receipt and sufficiency of which is hereby acknowledged, the parties hereby agree as follows:

ARTICLE I - THE ASSIGNMENT

1.1 In consideration of the mutual understandings set forth above and the financial terms set forth in the Sponsored Research Agreement between UNIVERSITY and ASSIGNEE, PSRF hereby assigns all of its right title and interest world-wide in the Joint IP to ASSIGNEE and ASSIGNEE's successor(s). PSRF hereby further assigns, transfers, and sets over unto ASSIGNEE, PSRF's entire right, title, and interest world-wide in and to said Joint IP in each and every country foreign to the United States; and PSRF further conveys to ASSIGNEE all world-wide priority rights resulting from the assignment of the Joint IP. PSRF agrees, at ASSIGNEE's expense, to execute all papers, give any required testimony, and perform other lawful acts, as ASSIGNEE may require to enable ASSIGNEE to perfect ASSIGNEE's interest in any resulting patent of the United States and countries foreign thereto, and to acquire, hold, enforce, convey, and uphold the validity of said patent and reissues and extensions thereof, and ASSIGNEE's interest therein.

1.2 ASSIGNEE and ASSIGNEE's successors grant to PSRF a nonexclusive, royalty-free, nonassignable, nonsublicensable personal license to practice the Joint IP for UNIVERSITY's own internal noncommercial educational research.

1.3 This Assignment Agreement shall not be construed to confer any rights upon ASSIGNEE by implication, estoppel or otherwise to any technology owned or controlled by PSRF which is not specifically set forth in this Assignment Agreement.

ARTICLE II - INDEMNIFICATION

2.1 ASSIGNEE shall at all times indemnify, defend and hold PSRF, UNIVERSITY, their trustees, directors, officers, employees and affiliates, harmless against all claims, proceedings, demands and liabilities of any kind whatsoever, including legal expenses and reasonable attorneys' fees, arising out of the death of or injury to any person or persons or out of any damage to property, resulting from ASSIGNEE's production, manufacture, sale, use, lease, consumption, licensing, or enforcement of the Joint IP.

2.2 EXCEPT AS OTHERWISE EXPRESSLY SET FORTH IN THIS ASSIGNMENT AGREEMENT, PSRF, UNIVERSITY, THEIR TRUSTEES, DIRECTORS, OFFICERS, EMPLOYEES, AND AFFILIATES MAKE NO REPRESENTATIONS AND EXTEND NO WARRANTIES OF ANY KIND, EITHER EXPRESS OR IMPLIED, INCLUDING BUT NOT LIMITED TO WARRANTIES OF MERCHANTABILITY, FITNESS FOR A PARTICULAR PURPOSE, VALIDITY OF PATENT RIGHTS CLAIMS, ISSUED OR PENDING, AND THE ABSENCE OF LATENT OR OTHER DEFECTS, WHETHER OR NOT DISCOVERABLE. NOTHING IN THIS ASSIGNMENT AGREEMENT SHALL BE CONSTRUED AS A REPRESENTATION MADE OR WARRANTY GIVEN BY PSRF THAT THE PRACTICE BY ASSIGNEE OF THE INTELLECTUAL PROPERTY RIGHTS GRANTED HEREUNDER SHALL NOT INFRINGE THE PATENT RIGHTS OF ANY THIRD PARTY. IN NO EVENT SHALL PSRF, UNIVERSITY, THEIR TRUSTEES, DIRECTORS, OFFICERS, EMPLOYEES AND AFFILIATES BE LIABLE FOR INCIDENTAL OR CONSEQUENTIAL DAMAGES OF ANY KIND, INCLUDING ECONOMIC DAMAGE OR INJURY TO PROPERTY AND LOST PROFITS, REGARDLESS OF WHETHER PSRF SHALL BE ADVISED, SHALL HAVE OTHER REASON TO KNOW, OR IN FACT SHALL KNOW OF THE POSSIBILITY.

ARTICLE III - NON-USE OF NAMES

3.1 ASSIGNEE shall not use the names, images or trademarks of UNIVERSITY, PSRF, or any of their employees, or any adaptation thereof, in any advertising, promotional, securities, or sales literature without prior written consent obtained from PSRF.

ARTICLE IV - NOTICES AND OTHER COMMUNICATIONS

4.1 Any notice or other communication pursuant to this Assignment Agreement shall be sufficiently made or given on the date of mailing if sent to such party by certified or registered first class mail, postage prepaid, addressed to it at its address below or as it shall designate by written notice given to the other party as follows:

In the case of THE PENN STATE RESEARCH FOUNDATION:

President
The Penn State Research Foundation
c/o Office of Technology Management
113 Technology Center
University Park, PA 16802-7000

In the case of ASSIGNEE:

Xerox Corporation
Associate General Counsel
Xerox Square, XRX2-20A
Rochester, NY 14644

ARTICLE V - MISCELLANEOUS PROVISIONS

5.1 Entire Assignment Agreement. This Assignment Agreement embodies the entire understanding of the parties and shall supersede all previous communications, representations, or undertakings, either verbal or written, between the parties relating to the subject matter hereof, except the Xerox-PSU Sponsored Research Agreement (Agreement Number 145376) having an Effective Date of July 20, 2012.

5.2 Amendment. This Assignment Agreement may be amended only by a written agreement embodying the full terms of the amendment signed by authorized representatives of both parties.

5.3 Severability. Should any provision of this Assignment Agreement be held to be illegal, invalid or unenforceable, by any court of competent jurisdiction, such provision shall be modified by such court in compliance with the law and, as modified, enforced. The remaining provisions of this Assignment Agreement shall be construed in accordance with the modified provision and as if such illegal, invalid or unenforceable provision had not been contained herein.

5.4 No Strict Construction. The language used in this Assignment Agreement shall be deemed to be the language chosen by both parties to express their mutual intent and no rule of strict construction against either party shall apply to any term or condition of this Assignment Agreement.

5.5 Relationship of Parties. Nothing contained in this Assignment Agreement shall be construed as creating a partnership, joint venture, agency or an association of any kind.

5.6 No Waiver. The failure of one party to enforce at any time any of the provisions of this Assignment Agreement, or any rights in respect thereto, or to exercise any election provided, shall in no way be considered to be a waiver of such provision, rights or elections or in any way to affect the validity of this Assignment Agreement, or excuse a similar subsequent failure to perform any such term or condition by the other party. Any waiver must be in writing.

5.7 Headings. The headings of several sections contained in this Assignment Agreement are inserted for convenience of reference only, and are not intended to be a part of or to affect the meaning or interpretation of this Assignment Agreement.

5.8 Governing Law. This Assignment Agreement shall be governed by and construed in accordance with the laws of the Commonwealth of Pennsylvania without giving effect to any choice of law or conflict of law provision or rule that would cause the application of the laws of any jurisdiction other than the Commonwealth of Pennsylvania, except that questions affecting the construction and effect of any patent shall be determined by the law of the country in which the patent was granted.

IN WITNESS WHEREOF, the parties, intending to be legally bound hereby, have each caused a duly authorized representative to execute this Assignment Agreement on the day and year set forth below.

XEROX CORPORATION

By: ______________________

Name: Sophie Vandebroek

Title: Xerox CTO, President XIG

Date: 2/11/13

THE PENN STATE RESEARCH FOUNDATION (PSRF)

By: ______________________

Name: David E. Branigan

Title: Treasurer

Date: 2/6/13

Invention Disclosure Number: 2012-3983 "Anomaly Detection Using a Kernel-Based Sparse Reconstruction Model"

INVENTION ASSIGNMENT

FOR VALUE RECEIVED, and pursuant to my obligations under our (my) employment agreements/appointments with THE PENNSYLVANIA STATE UNIVERSITY ("University"), we Vishal Monga and Xuan Mo, hereby sell, assign and transfer unto the University's designee, THE PENN STATE RESEARCH FOUNDATION, as assignee, and its successors, assigns and legal representatives, the entire right, title and interest in and to all subject matter invented by me and disclosed in a Penn State University invention disclosure number 2012-3983 signed by me on the date set forth below and entitled "Anomaly Detection Using a Kernel-Based Sparse Reconstruction Model" (the "Invention") the substance and entirety of which is attached hereto as Exhibit A, including the rights to any patents, whether United States or foreign, which at anytime may be granted therefor, including any and all continuations, continuations-in-part, divisions, reissues, renewals, extensions, substitutions, additions or reexaminations of such patent.

We, request that any and all patents for said inventions be issued to said assignee, its successors, assigns and legal representatives, or to such nominees as it may designate.

We agree that, when requested, we will, without charge to said assignee but at its expense, sign all papers, take all rightful oaths, and do all acts which may be necessary, desirable or convenient for securing, maintaining and enforcing patents for said inventions in any and all countries and for vesting title thereto in said assignee, its successors, assigns and legal representatives or nominees.

We authorize and empower the said assignee, its successors, assigns and legal representatives or nominees, to invoke and claim for any application for patent or other form of protection for said inventions filed by it or them, the benefit of the right of priority provided by the International Convention for the Protection of Industrial Property, as amended, or by any convention which may henceforth be substituted for it, and to invoke and claim such right of priority without further written or oral authorization from us.

We hereby consent that a copy of this assignment shall be deemed a full legal and formal equivalent of any assignment, consent to file or like document which may be required in any country for any purpose and more particularly in proof of the right of said assignee or nominee to claim the aforesaid benefit of the right of priority provided by the International Convention for the Protection of Industrial Property, as amended, or by any convention which may henceforth be substituted for it.

We covenant with said assignee, its successors, assigns and legal representatives, that the rights and property herein conveyed are free and clear of any encumbrance, and that we have full right to convey the same as herein expressed.

STATE OF PENNSYLVANIA :
: ss:
COUNTY OF CENTRE :

On this 28th day of November, 2012, before me, a Notary Public in and for the county and State aforesaid, appeared Vishal Monga and Xuan Mo, to me personally known to be the person whose name is subscribed to the foregoing instrument, and acknowledged that he executed said instrument as his free and voluntary act for the uses and purposes therein expressed.

Witness my hand and seal the day and year last above given.

Donna A. Jones
Notary Public

[Page 1 of 2 – Signatures Continued on Page 2]

COMMONWEALTH OF PENNSYLVANIA
Notarial Seal
Donna A. Jones, Notary Public
State College Boro, Centre County
My Commission Expires April 18, 2015
MEMBER, PENNSYLVANIA ASSOCIATION OF NOTARIES

Signed at University Park, Pennsylvania, this 28th day of November, 2012.

Witness: Diane Keshvari Signed: Vishal Monga

STATE OF PENNSYLVANIA :
: ss:
COUNTY OF CENTRE :

On this 28th day of November, 2012, before me, a Notary Public in and for the county and State aforesaid, appeared Vishal Monga and Yuan Ma, to me personally known to be the person whose name is subscribed to the foregoing instrument, and acknowledged that he executed said instrument as his free and voluntary act for the uses and purposes therein expressed.

Witness my hand and seal the day and year last above given.

Donna A. Jones
Notary Public

COMMONWEALTH OF PENNSYLVANIA
Notarial Seal
Donna A. Jones, Notary Public
State College Boro, Centre County
My Commission Expires April 18, 2015
MEMBER, PENNSYLVANIA ASSOCIATION OF NOTARIES

Signed at University Park, Pennsylvania, this 28th day of November, 2012.

Witness: Diane Keshvari Signed: Yuan Ma

Please see the attachment, considered Appendix A, the Technology Disclosure Form for PSU invention disclosure 2012-3983 "Anomaly Detection Using a Kernel-Based Sparse Reconstruction Model".

PENNSTATE

Technology Disclosure Form

Office of Technology Management
113 Technology Center, University Park, PA 16802
814.865.6277 p · 814.865.3591 f · otminfo@psu.edu

Disclosure Number (OTM Use Only)
2012-3983

Original signed form should be submitted to the OTM via your research dean or appropriate administrative unit. We encourage you to concurrently send a signed or unsigned copy electronically directly to the OTM. If possible please submit form at least one month prior to any public disclosure (including web abstracts). See attached guidelines/instructions or contact OTM for assistance. If additional space is needed, attach a separate sheet of paper.

1. Title of Invention/Technology (brief & non-confidential):

Anomaly detection using a kernel-based sparse reconstruction model

2. Please Attach a Detailed Description of Technology (see instructions on page 4):

3. Disclosers/Inventors (please list the primary contact first – attach additional sheets for more than 5):

	Full Legal Name	Title (e.g. "Professor")	Dept. or Affiliation	Inv %
A	Vishal Monga	Assistant Professor	Electrical Engineering	25%
B	Xuan Mo	Graduate Research Assistant (Student)	Electrical Engineering	25%
C	Raja Bala	Principal Scientist	Xerox Research Center Webster	25%
D	Zhigang Fan	Principal Scientist	Xerox Research Center Webster	25%
E				

4. Contact Information:

	Department Address	Home Address	Email Address & Phone #
A	111 J Electrical Engineering West	772 Tanager Dr, State College, PA	vmonga@engr.psu.edu, 814-863-1267
B	104 Electrical Engineering East	10Vairo Blvd, Apt. 214B, State College, PA, 16803	xym5016@psu.edu, 814-867-4564
C	800 Phillips Road, MS 128-27E, Webster, NY 14580	48 Woodgreen Drive, Pittsford, NY 14534	Raja.bala@xerox.com, 585-265-7838
D	800 Phillips Road, MS 128-27E, Webster, NY 14580	153 Yorktown Drive, Webster, NY 14580	Zhigang.fan@xerox.com, 585-422-6072
E			

5. Disclosure Execution (required for PSU employees only):

	Name	Signature	Citizenship	Date (m/d/yyyy)
A	Vishal Monga	[signature]	India	09/20/2012
B	Xuan Mo	Xuan Mo	China	09/20/2012
C				
D				
E				

6. Witness: (who has read and understands the disclosure

Printed Name:		Signature:		Date:	

7. Research Dean or Administrative Officer:

Printed Name:		Signature:		Date:	

PENNSTATE

Technology Disclosure Form

Office of Technology Management
113 Technology Center, University Park, PA 16802
814.865.6277 p · 814.865.3591 otminfo@psu.edu

Disclosure Number (OTM Use Only)

8. Record of Invention:

	Event	Date	References (e.g. lab notebooks)
A	Conception of Invention:	Aug, 2012	Document:
B	Algorithm of Invention:	Aug, 2012	Document:
C	Date of Reduction to Practice:	September 2012	Document:
D			Main document: PSU_Xerox_ID_Kernel_Sept17_V4.docx

9. Obligations to Third Parties:

A. Is this technology the result of sponsored research (either government or industry)? Yes X No

	Sponsor:	OSPOSP/ORA Grant #, Contract #, or Agreement #	Principal Investigator
1	**Xerox Corporation**	**Sponsored Research Agreement #145376**	**Raja Bala**
2			
3			

B. Are there any other agreement(s) pertaining to the technology? (include: materials bailment/transfer, consulting, confidentiality, grant-in-aid, etc.) Yes X No

	Agreement Type	Name of Other Party	Contact
1	**Confidential Disclosure Agreement**	**Xerox Corporation**	**Raja Bala**
2			
	Please attach copies of any third party agreements		

10. Public Disclosures (any publicly available and potentially enabling description – see guidelines, pg 4):

	Disclosure Type (please attach copies)	Yes	No	Date (m/d/yyyy)	Citation and/or Explanation
A	Has the technology been published or a manuscript been submitted for publication?		X		
B	If not, will a manuscript for the technology be submitted in the future? Approx. when?	X		**November 2012**	**IEEE Transactions**
C	Has the technology been described in a thesis, or will it be described in a thesis?	X		**May 2014**	**Will be a part of Xuan Mo's PhD Thesis**
D	Has the technology been presented in a public forum (e.g. speech, conference, poster, etc.)?		X		
E	Are there any other past or future enabling publications (e.g. online postings)?	X			**IEEE Asilomar Conference Nov 4-7, 2012**

11. Descriptive Keywords (to be used for patent or background searching and/or marketing):

video anomaly detection	**kernel**	**Sparse reconstruction**	**dictionary**

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Technology Disclosure Form

Office of Technology Management
113 Technology Center, University Park, PA 16802
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Disclosure Number (Use Only)

Please attempt to answer the following questions. In addition to the detailed description that you attach, this information will assist in our assessment of the technology and may increase the likelihood of patenting and commercialization success.

12. Stage of Development: Briefly describe the status of the technology's development. Which of the following terms best describe its stage of development: concept proof of concept, prototype, working model, demo, fully developed? Are samples, a prototype, or a demo available to share with prospective licensees?

A working prototype has been built to illustrate the concept. Sample data and results are available and can be shared upon request.

13. Please briefly describe the problem that the technology solves and its advantages/benefits relative to competing technologies or products. What product might this invention become?

The technology is aimed at detecting anomalies or unusual patterns in video footage in the transportation domain. Examples of such anomalies include traffic violations, accidents, unsafe driver behavior, street crime, and other suspicious activities. The approach is built upon a new mathematical framework called joint sparse reconstruction, which in turn requires the existence of a dictionary comprising classes of normal events. The success of the sparsity-based approach relies upon a dictionary with good inter-class separation, which is not guaranteed especially in complex traffic scenarios. The kernel transform is a method to improve inter-class separability, and thus offer superior and more robust anomaly detection performance. Other benefits of the approach over existing techniques include the ability to detect joint multi-object anomalies and increased robustness with respect to effects such as noise and occlusion. The invention would be used in a video-based traffic surveillance system as a means of detecting and flagging unusual activities at a transportation site such as a traffic intersection, parking lot, or highway.

14. Please list key prior art references:

Piciarelli et al., "Trajectory-based anomalous event detection," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 18, no. 11, pp. 1544–1554, 2008.

Li, et al. "Abnormal behavior detection via sparse reconstruction analysis of trajectory," in IEEE (ICIG), Sixth International Conference on, aug. 2011, pp. 807–810.

Scholkopf and Smola, Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond, The MIT Press, 2001.

[A complete list of references appears in the attached detailed description of the invention]

15. Please list the companies or industries that are most likely to be interested in licensing this technology:

Primary business interest is for commercialization within Xerox	

16. Please list any contacts that you have (and their contact information) that we may approach in our marketing efforts (to learn more about the market potential of the technology or to reach potential licensees):

17. Please check the reason(s) that best describe why you submitted this invention disclosure:

X	I/we believe that the invention has significant commercial potential
	I/we believe that this invention is a platform and/or pioneering technology
	I/we are aware of a specific company that is interested in licensing the technology
	I/we are interested in being involved with a startup company based on this technology
X	To comply with the requirements of an existing research agreement and/or University policy
	Other (please specify):

Invention Disclosure:

Anomaly Detection using a Kernel-based Sparse Reconstruction Model

Vishal Monga, Xuan Mo (Pennsylvania State University)
Raja Bala, Zhigang Fan (Xerox Corporation)

1. Introduction

With an increasing demand for security and safety, video-based surveillance systems are being increasingly used in urban locations. Vast amounts of video footage are collected and analyzed for traffic violations, accidents, crime, terrorism, vandalism, and other suspicious activities. Since manual analysis of such large volumes of data is prohibitively costly, there is a desire to develop effective algorithms that can aid in the automatic or semi-automatic interpretation and analysis of video data for surveillance and law enforcement. An active area of research within this domain is video anomaly detection, which refers to the problem of finding patterns in data that do not conform to expected behavior, and that may warrant special attention or action. The focus of this invention is in the detection of anomalies in the transportation domain. Examples include traffic violations, unsafe driver and pedestrian behavior, accidents, etc. Fig. 1 shows some examples of transportation related anomalies.

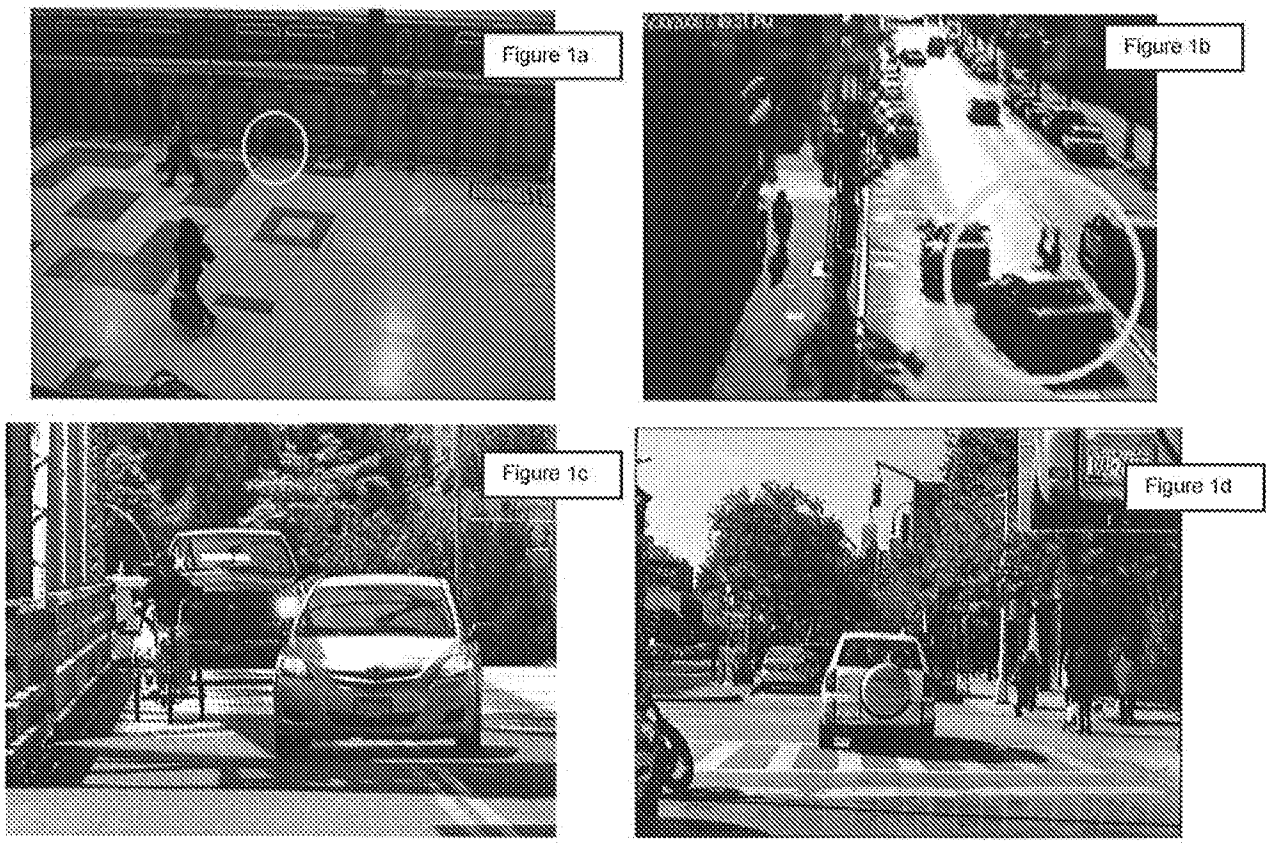

Fig. 1 Examples of traffic-related anomalies: (a) unattended baggage; (b) car approaching a pedestrian; (c) crossing the yellow line; (d) running a red light.

Video-based anomaly detection (AD) has received much recent attention. An excellent overview of techniques can be found in Ref [1]. One class of techniques relies upon object tracking to detect nominal object trajectories and deviations thereof. This approach is appealing for traffic-related anomalies since there are many state-of-the-art tracking techniques that can be leveraged [2]. A common approach is to derive nominal vehicle paths and look for deviations thereof in live traffic video data [3-6]. During the test or evaluation phase, a vehicle is tracked and its path compared against the nominal classes. A statistically significant deviation from all classes indicates an anomalous path.

Primary challenges in anomaly detection include: i) Successful detection of abnormal patterns in realistic scenarios involving multiple object trajectories in the presence of occlusions, clutter, and other background noise; ii) development of algorithms that are computationally simple enough to detect anomalies in quasi-real-time; iii) the lack of sufficient and standardized data sets, particularly those capturing anomalous events which are rare by definition.

2. Background: Sparsity based Anomaly Detection

Recently a new breed of techniques based on sparse reconstruction has been successfully applied towards the classification problem [7] and subsequently for anomaly detection [8]. The basic idea is as follows. In a training step, normal or usual events in the video footage are extracted and categorized into a set of nominal event classes. The categorization is based on a set of n-dimensional feature vectors extracted from the video data, and can be performed manually or automatically. In [8], the parametric representations of vehicle trajectories are chosen as the features. The basic premise underlying sparse reconstruction is that any new nominal sample can be well explained by a linear combination of samples within one of the nominal classes.

We now elaborate on the sparse reconsruction model, as it forms the basis for the invention. Arrange the T training samples from the i-th class as the columns of a matrix $\mathbf{A}_i \in \mathbb{R}^{n\times T}$. The dictionary $\mathbf{A} \in \mathbb{R}^{n\times KT}$ of training samples from all K classes is then formed as follows: $\mathbf{A} = [\mathbf{A}_1, \mathbf{A}_2, \ldots, \mathbf{A}_K]$. Given sufficient training samples from the m-th trajectory class, a test image $\mathbf{y} \in \mathbb{R}^n$ from the same class is conjectured to approximately lie in the linear span of those training samples. Any input trajectory feature vector may hence be represented by a sparse linear combination of the set of all training trajectory samples as follows:

$$\mathbf{y} = \mathbf{A}\boldsymbol{\alpha} = [\mathbf{A}_1, \mathbf{A}_2, \ldots, \mathbf{A}_K]\begin{bmatrix}\boldsymbol{\alpha}_1\\ \boldsymbol{\alpha}_2\\ \vdots\\ \boldsymbol{\alpha}_K\end{bmatrix} \qquad (1)$$

where each $\alpha_i \in \mathbb{R}^T$. Typically for a given trajectory y, only *one* of the α_i's would be active (corresponding to the class/event that y is generated from), thus the coefficient vector $\alpha \in \mathbb{R}^{KT}$ is modeled as being sparse, and is recovered by solving the following optimization problem:

$$\hat{\alpha} = \arg\min_{\alpha} \|\alpha\|_1 \quad \text{subject to} \quad \|y - A\alpha\|_2 < \varepsilon \tag{2}$$

where the objective is to minimize the number of non-zero elements in α. It is well-know from the compressed sensing literature that using the ℓ_0 norm, leads to an NP-hard problem. Thus the ℓ_1 norm is used as an effective approximation. The residual error between the test trajectory and each class behavior pattern is computed to find the class to which the test trajectory belongs:

$$r_i(y) = \|y - A_i\hat{\alpha}_i\|_2 \quad i = 1, 2, \ldots, K \tag{3}$$

If anomalies have been predefined into their own class, then the classification task also accomplishes anomaly detection. Alternatively, if all training classes correspond to nominal events, then anomalies can be identified via outlier detection. To this end, an index of sparsity is defined and used to measure the sparsity of the reconstructed α [7]:

$$SCI(\alpha) = \frac{K \cdot \max_i \|\delta_i(\alpha)\|_1 / \|\alpha\|_1 - 1}{K - 1} \in [0, 1] \tag{4}$$

where $\delta_i(\alpha): \mathbb{R}^T \to \mathbb{R}^T$ the characteristic function that selects the coefficients α_i with respect to the i-th class. It is readily seen that nominal samples are likely to exhibit a high level of sparsity, and conversely, anomalous samples will likely produce a low sparsity index. A threshold on $SCI(\alpha)$ determines whether or not the sample is anomalous.

Recently, a joint sparsity model has been developed by the same inventors, that successfully detects anomalies involving co-occurrence of two or more events [14].

A primary advantage of the sparsity based framework for classification and anomaly detection over other techniques is that it has been shown to be particularly robust against various distortions, notably occlusion. It has also been shown to be robust with respect to the particular features chosen, provided the sparse representation is computed correctly.

One potential limitation of the approach is that the effectiveness of the sparsity model largely relies on the structure of training data. If the event classes are not sufficiently linearly separable, the sparse reconstruction may not result in accurate anomaly detection.

3. Detailed Description of the Invention

In this invention, we propose incorporating a kernel function into the sparse reconstruction model to afford better inter-class separability, and thus superior anomaly detection performance. Kernel-based algorithms are often used to improve performance of classification algorithms, such as support vector machines [10]. The basic idea is to project the non-separable data into a high dimensional nonlinear feature space in which the data becomes more linearly separable.

Essentially, a kernel function exploits the higher-order nonlinear structure of the data that is not captured by linear models.

Specifically, define a kernel function $\kappa : \mathbb{R}^n \times \mathbb{R}^n \mapsto \mathbb{R}$ as the inner product of two functions: $\kappa(x, z) = \langle \Phi(x), \Phi(z) \rangle$. (This is a common form of kernel used in SVM classifiers [12].) Some common kernel functions include:

1) Gaussian radial basis function(RBF): $\kappa(x, z) = e^{-\gamma\|x-z\|^2}$, for $\gamma > 0$
2) Homogeneous polynomial kernel: $\kappa(x, z) = (x \cdot z)^d$
3) Inhomogeneous polynomial kernel: $\kappa(x, z) = (x \cdot z + 1)^d$

After using the kernel function, the training data is projected into another more linearly separable space: $a_i \mapsto \Phi(a_i)$, where a_i is the i-th column of A. Let $\Phi(y)$ denote the representation of the test trajectory in this space.

The test trajectory can now be represented as follows:

$$\Phi(y) = [\Phi(a_1) \ \dots \ \Phi(a_{KP})][\alpha'_1 \ \dots \ \alpha'_{KP}]^T = A_\Phi \alpha' \qquad (5)$$

where α' is also assumed to be sparse.

Similar to Eq. (2), the new sparse coefficient vector $\alpha' \in \mathbb{R}^{KP}$ can be recovered by solving:

$$\hat{\alpha}' = \underset{\alpha}{\operatorname{argmin}} \ \|\alpha'\|_1 \quad \text{subject to} \quad \|\Phi(y) - A_\Phi \alpha'\|_2 < \varepsilon \qquad (6)$$

Let $\Theta_A \in \mathbb{R}^{n \times n}$ be the kernel matrix whose (i, j)-th entry is $\kappa(a_i, a_j)$ and $\theta_{A,y} \in \mathbb{R}^n$ be the vector whose i-th entry is $\kappa(a_i, y)$, the correlation (dot product) between a pixel $\Phi(y)$ and a dictionary atom $\Phi(a_i)$ is then computed by:

$$c_i = \langle \Phi(y), \Phi(a_i) \rangle = \kappa(a_i, y) = (\theta_{A,y})_i \qquad (7)$$

the orthogonal projection coefficient of $\Phi(y)$ onto a set of selected dictionary atoms $\{\Phi(a_n)\}_{n \in \Lambda}$ is given as:

$$p_\Lambda = ((\Theta_A)_{\Lambda,\Lambda})^{-1} (\theta_{A,y})_\Lambda \qquad (8)$$

and the residual vector between $\Phi(y)$ and its approximation using the selected atoms $\{\Phi(a_n)\}_{n \in \Lambda} = (A_\Phi)_{:,\Lambda}$ is then expressed as:

$$\Phi(r) = \Phi(x) - (A_\Phi)_{:,\Lambda} ((\Theta_A)_{\Lambda,\Lambda})^{-1} (\theta_{A,y})_\Lambda \qquad (9)$$

The correlation between $\Phi(r)$ and an atom $\Phi(a_i)$ can be computed by:

$$c_i = \langle \phi(y), \phi(a_i) \rangle = (\Theta_{Ay})_i - (\Theta_A)_{i,\Omega}((\Theta_A)_{\Omega,\Omega})^{-1}(\Theta_{Ay})_\Omega \quad (10)$$

Also, the residue of i-th class becomes:

$$r_i(y) = \left(\kappa(y,y) - 2\alpha'^T_{\Omega_i}(\Theta_{Ay})_{\Omega_i} + \alpha'^T_{\Omega_i}(\Theta_A)_{\Omega_i,\Omega_i}\alpha'_{\Omega_i}\right)^{\frac{1}{2}} \quad (11)$$

where Ω_i is the index set associated with the i-th training class.

Therefore, by extending the Orthogonal Matching Pursuit (OMP)[12], the row sparsity model with kernel function can be solved using Algorithm 1 (See Appendix)

It is important to choose a good form and parameterization of the kernel function. In the field of machine learning, the optimal kernel is often chosen experimentally.

In our preferred embodiment, we apply the Gaussian RBF kernel function to our data, but with the best parameterization. Specifically, $\kappa(x, z) = e^{-\gamma\|x-z\|^2}$ is chosen to be the kernel function, and we desire the best parameter γ. To this end, multiple training dictionaries $A_\phi(\gamma)$ are generated for different choices of γ. Inspired by the technique of cross-validation, we split the training data $A_\phi(\gamma)$ into two subsets $B_\phi(\gamma)$ and $C_\phi(\gamma)$, such that both $B_\phi(\gamma)$ and $C_\phi(\gamma)$ have representation from the K classes. Now if the dictionary in the sparsity model is chosen to be equal to $B_\phi(\gamma)$ and a (transformed) test trajectory is picked from $C_\phi(\gamma)$, then ideally we expect perfect classification into one of the K classes. Therefore, a good kernel is one that will enable close to ideal classification of test samples from $C_\phi(\gamma)$) - which means that only a small number of $\alpha'_j(\gamma)$ are activated (non-zero) and for one particular class. Recall the outlier rejection measure:

$$SCI(\alpha'_j(\gamma)) = \frac{K \cdot \max_i \|\delta_i(\alpha'_j(\gamma))\|_1 / \|\alpha'_j(\gamma)\|_1 - 1}{K-1} \quad (12)$$

where $\delta_i(\alpha'_j(\gamma))$ is the vector whose only nonzero entries are the same as those in $\alpha'_j(\gamma)$ associated with class i. $SCI(\alpha'_j(\gamma))$ takes on values close to 1 if the classification is accurate. Therefore the best γ can be chosen by solving the following kernel parameter optimization problem:

$$\hat{\gamma} = \underset{\gamma}{\arg\max} \sum_j SCI(\alpha'_j(\gamma)) \quad (13)$$

In summary, the feature space of the single-object sparsity model has been modified by an appropriate kernel function. We conjecture that the new feature space will be more linearly separable, and hence it will enable the sparsity model to detect anomalies with higher accuracy.

The aforementioned kernel formulation can be extended to the multi-object joint sparsity model in a relatively straightforward manner.

4. Experimental Results

We first employ the CAVIAR standard video data set to evaluate our approach. This data set comprises trajectories of people walking across a public atrium. An example of CAVIAR data can be seen in Fig. 2, a man suddenly falls on the floor, when walking across the lobby.

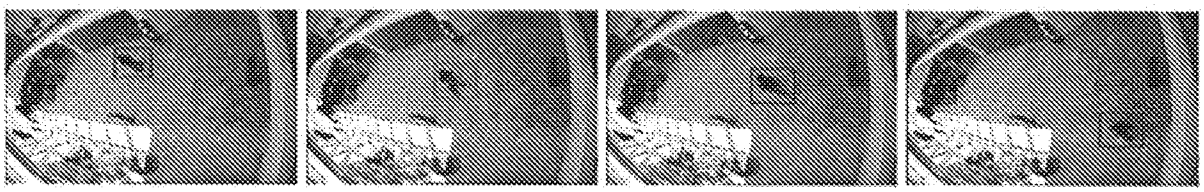

Fig. 2. A man suddenly falls on floor from CAVIAR data set

The training dictionary consists of 10 normal trajectory classes and 3 anomalous trajectory classes, and each class contains 10 trajectories. 21 normal trajectories and 19 anomalous trajectories are used as independent test data. Because anomalous events are well-represented in this database, we train a separate anomalous class, and Eqn (3) is used to classify both normal and anomalous test trajectories. We compare our approach (abbreviated to JKSM) with one of the state of the art algorithms [3]. The confusion matrices of the approach in [3] are compared with the original sparsity model and kernel-based sparsity model in Table I. We note first that the superior performance of the sparsity model over Piciarelli's approach is significant and attributed to the merits of sparse reconstruction in solving the classification problem. Secondly, and more importantly, we observe that the kernel serves to further increase the identification accuracy.

Table I Confusion matrices on CAVIAR data

	Piciarelli et al.[3]		Li et al.[8]		JKSM	
	Normal	Anomaly	Normal	Anomaly	Normal	Anomaly
Normal	85.7%	26.3%	90.5%	15.8%	95.2%	10.5%
Anomaly	14.3%	73.7%	9.5%	84.2%	4.8%	89.5%

We generate receiver operating characteristic (ROC) curves on the same data. Figs. 3 reveals that the proposed kernel-based method outperforms the original sparsity model and that of Piciarelli et al. by a considerable margin.

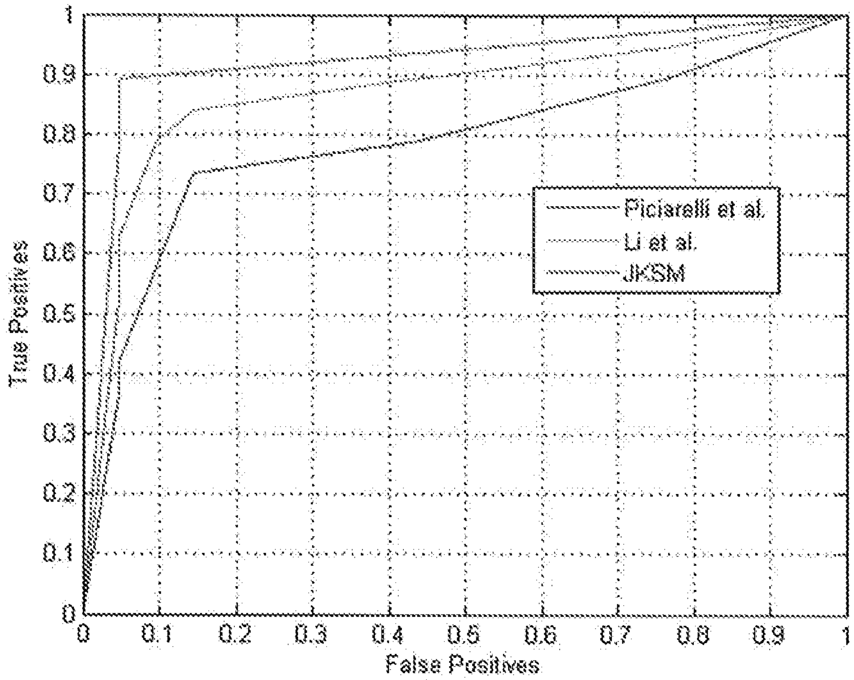

Fig. 3. ROC curves of 3 different methods on CAVIAR data

We then test our algorithm on Xerox Intersection data. Fig 4 shows an example of Xerox Intersection data: a car fail to yield to oncoming car while turning left.

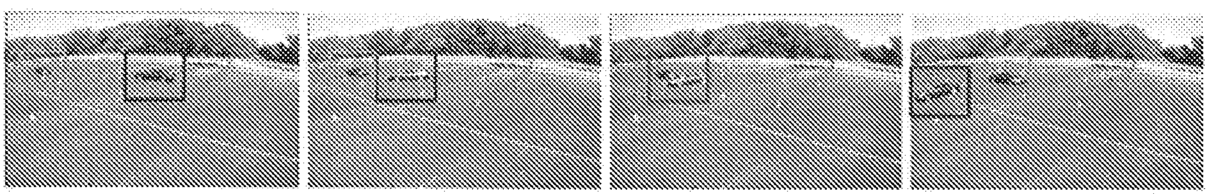

Fig. 4. A car fails to yield to oncoming car while turning left from Xerox Intersection data set

In Xerox Intersection data, there are 6 different 2-object normal event classes (containing 6 trajectory pairs each) and 6 different anomalous classes (containing 4 trajectory pairs each). 17 normal trajectory pairs and 14 anomalous trajectory pairs are used for testing. The confusion matrices of our method against the two competing trajectory based techniques are shown in Table II. And the ROC curves are shown in Fig. 5.

Table III Confusion matrices on Xerox Intersection data

	Piciarelli et al. 1		Piciarelli et al. 2		Han et al.[15]		JKSM	
	Normal	Anomaly	Normal	Normal	Normal	Anomaly	Normal	Anomaly
Normal	58.8%	7.1%	94.1%	64.3%	82.4%	35.7%	88.2%	14.3%
Anomaly	41.2%	92.9%	5.9%	35.7%	17.6%	64.3%	11.8%	85.7%

Since the one class SVMs method in Piciarelli et al. does not capture the interaction between objects, thus it can only be used for single-object anomaly detection. In order to see the its performance, we heuristically define 2 extended version of Piciarelli et al. approaches:

1. Identification both events separately. If either of these two events is anomaly, we assume that this joint event is anomalous. (refer to as Piciarelli et al._1)
2. Identification both events separately. Only if both two events are anomalies, we assume this joint event is anomalous. (refer to as Piciarelli et al._2)

In this case, we separate every 2-object event into 2 individual events as the training for Piciarelli et al._1 and Piciarelli et al._2. The improvement over the technique of Piciarelli et al. is expected since this technique is really for single-object anomaly detection.

In [15] anomalies are detected by the use of context based rules on the result of multiple-object tracking. This puts an unreasonable burden on defining these rules and is often restrictive in practice, i.e. not all anomalies can be anticipated. In the proposed joint sparsity model, interactions between distinct object trajectories are better captured and departures from expected "joint behavior" (particularly in the case training for anomalies is absent/limited) is employed which enables the improvement in detection rates.

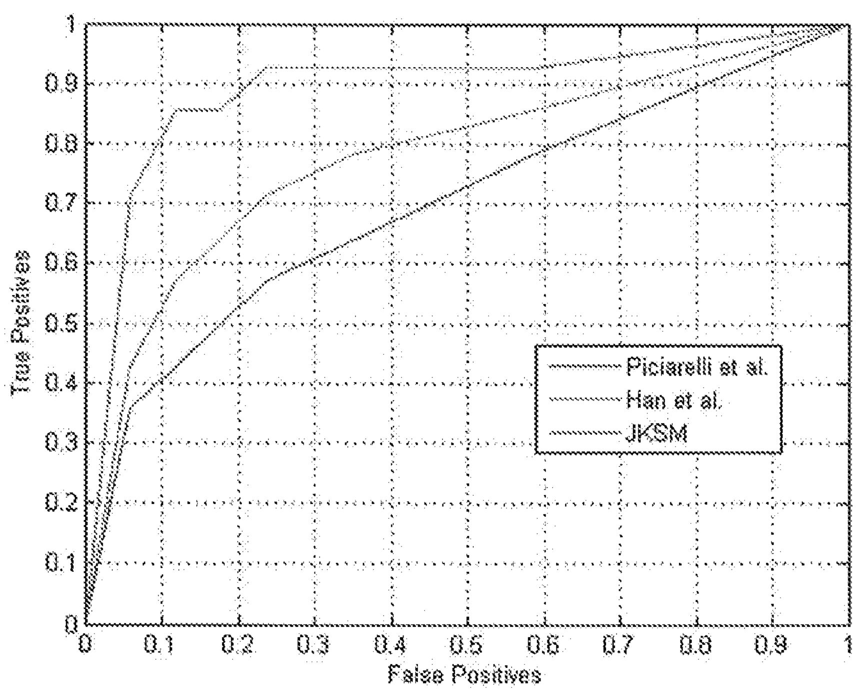

Fig. 5. ROC curves of 3 different methods on Xerox Intersection data

5. Outline of Main Claim

What is claimed is a method/system for detecting anomalies in transportation related video footage, the method/system comprising:

- Constructing a dictionary of a plurality of event classes, wherein events are defined as n-dimensional feature vectors
- Defining a nonlinear kernel function that effectively transforms the n-dimensional feature vectors into a higher dimensional feature space
- Receiving test events within an input video sequence
- Determining whether or not the test event is anomalous by applying sparse reconstruction with respect to the training dictionary in the higher dimensional feature space induced by said nonlinear kernel function

Subclaims will expand on each of the elements, such as choice of kernel, and details of the last step.

6. References

1. Saligrama et al., "Video Anomaly Identification," *IEEE Signal Processing Magazine*, vol. 27, no. 5, pp. 18-33, September 2010.
2. Yimaz et al., "Object tracking – a survey", *ACM Computing Surveys*, Vol. 38, No. 4, Article 13, December 2006.
3. C. Piciarelli, C. Micheloni, and G. Foresti, "Trajectory-based anomalous event detection," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 18, no. 11, pp. 1544– 1554, 2008.
4. W. Hu, T. Tab, L. Wang, and S. Maybank, "A survey on visual surveillance of object motion and behaviors," *IEEE Trans. Syst. Man Cybern.*, vol. 34, no. 3, pp. 334–352, 2004.
5. Junejo et al., "Multi Feature Path Modeling for Video Surveillance", in *Proc. IEEE Int. Conf. Pattern Recognition*, vol. 2, pp. 716–719, Aug. 2004.
6. Zhouyu Fu, Weiming Hu and Tieniu Tan, "Similarity based vehicle trajectory clustering and anomaly detection", *IEEE International Conference on Image Processing*, 2005 (ICIP'05), vol. 2, pp: 602-605, 2005.
7. J. Wright et al, "Robust Face Recognition via Sparse Representation", *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 31, no. 2, pp. 210-227, Feb. 2009.
8. C. Li et al, "Abnormal Behavior Detection via Sparse Reconstruction Analysis of Trajectory", *Proc. IEEE 6th Int. Conf on Image & Graphics*, pp. 807-810, 2011.
9. SJ. A. Tropp et al, "Algorithms for simultaneous sparse approximation. Part I: Greedy pursuit," *Elsevier Signal Process.—Special Issue on Sparse Approximations in Signal and Image Processing*, vol. 86, no. 3, pp. 572–588, Mar. 2006.

10. B. Scholkopf and A. J. Smola, Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond, The MIT Press, 2001.

11. Bernhard E. Boser, Isabelle M. Guyon, and Vladimir N. Vapnik, "A training algorithm for optimal margin classifiers," in Proceedings of the fifth annual workshop on Computational learning theory, New York, NY, USA, 1992, COLT '92, pp. 144–152, ACM.

12. J.A. Tropp and A.C. Gilbert, "Signal recovery from random measurements via orthogonal matching pursuit," Information Theory, IEEE Transactions on, vol. 53, no. 12, pp. 4655 – 4666, dec. 2007.

13. Ce Li, Zhenjun Han, Qixiang Ye, and Jianbin Jiao, "Abnormal behavior detection via sparse reconstruction analysis of trajectory," in IEEE Image and Graphics (ICIG), 2011 Sixth International Conference on, aug. 2011, pp. 807 –810.

14. Bala et al, "Method and system for automatically detecting multi-object anomalies utilizing joint sparse reconstruction model", U.S Patent Application 20120244.

15. M. Han, W. Xu, H. Tao, and Y. Gong, "An algorithm for multiple object trajectory tracking," in Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on, vol. 1, june-2 july 2004, pp. I–864 – I–871 Vol.1.

7. Appendix

Algorithm 1 KOMP

Input: Dictionary $\mathbf{A} = [a_1\ a_2\ \dots\ a_K]$, data vector y, kernel function κ, a stopping criterion

Initialization: compute the kernel matrices $\Theta_{\mathbf{A}}$ and $\theta_{\mathbf{A},y}$. Set index set $\Lambda_0 = \arg\max_i \| (\theta_{\mathbf{A},y})_{i,:} \|_2$ and iteration counter $t = 1$.

while stopping criterion has not been met **do**

1) Compute the correlation matrix

$$\mathbf{C} = \theta_{\mathbf{A},y} - (\Theta_{\mathbf{A}})_{:,\Lambda_{t-1}}((\Theta_{\mathbf{A}})_{\Lambda_{t-1},\Lambda_{t-1}} + \lambda \mathbf{I})^{-1}(\theta_{\mathbf{A},y})_{\Lambda_{t-1},:}$$

2) Select the new index as $\lambda_t = \arg\max_i \| \mathbf{C}_{i,:} \|_2$

3) Update the index set $\Lambda_t = \Lambda_{t-1} \cup \{\lambda_t\}$

4) $t \leftarrow t + 1$

end while

Output: Index set $\Lambda = \Lambda_{t-1}$, the sparse representation $\alpha' = (\Theta_{\Lambda,\Lambda} + \lambda \mathbf{I})^{-1}(\theta_{\mathbf{A},y})_{\Lambda,:}$