Smart Monitoring of Health Parameters

Mohammad Adibuzzaman

PhD Candidate
Marquette University

Advisor: Sheikh Iqbal Ahamed, PhD
Co-Advisor: Stephen Merrill, PhD
Committee Member: Dennis Brylow, PhD
Committee Member: Praveen Madiraju, PhD
Committee Member: Bhagwant Sindhu, PhD

April 7, 2015

Table of Contents

Motivation

Motivation

- Assessment of different health parameters including pain level, physiological parameters such as blood pressure, heart rate, and hemoglobin level is important for multiple medical conditions [Lucey, 2012; Scully, 2012]
- The validation of the algorithms are also needed for application in a clinical setting.
- With a rising cost of health care and increasing number of aging population we need affordable solutions for health care [Kaplan, 2006; Boulos 2011] and at the same time improve patient outcome.

.

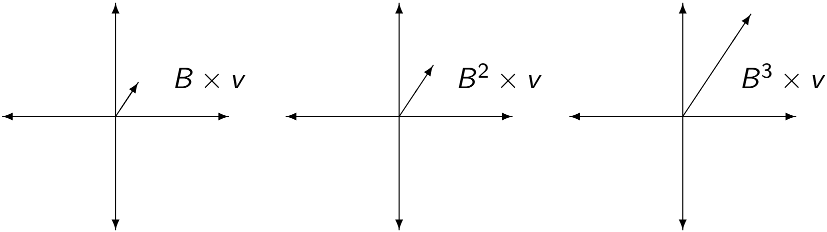
Background

Eigenvalues: Definition

Eigenvalue is defined as

$$B \times v = \lambda \times v$$

Eigenvalues have a very interesting property: when multiplied by the eigenvalue, eigenvectors do not rotate.



Eigenvalues Contd.

Any vector can be represented by a basis whose reference vectors are eigenvectors of the transition matrix.

$$B^i \times v = B^i \times v_1 + B^i \times v_2 = {\lambda_1}^i \times v_1 + {\lambda_2}^i \times v_2$$

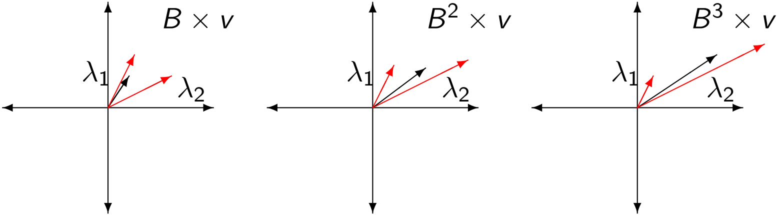


Figure: The eigenvectors corresponding to eigenvalues less than zero converge to zero when B is repeatedly applied. λ_1 is less than one and λ_2 is greater than one.

Principal Component Analysis (PCA)

PCA highlights the similarities and dissimilarities in a multidimensional data set.

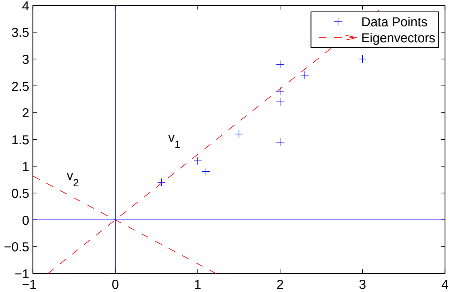


Figure: The red dashed lines represent the eigenvectors of the covariance matrix. v_1 is the Principal Component here.

Markov Chain

A Markov process is a mathematical process that transits from one state to the other and is considered memoryless.

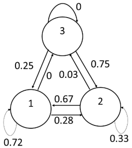


Figure: A simple Markov Chain with three states and their transition probabilities.

$$P = \begin{bmatrix} 0.72 & 0.28 & 0 \\ 0.67 & 0.30 & 0.03 \\ 0.25 & 0.75 & 0 \end{bmatrix}$$

Eigenvalues of Markov Chain

- For any transition probability matrix of a markov chain, there exists an unique eigenvector, π for which the eigenvalue is 1.
- Because all the other eigenvalues are less than one, after n steps, where n is sufficiently large, the stationary distribution contains only the eigenvector corresponding to one.

$$P \times \pi = \pi$$

- For a 2×2 matrix,

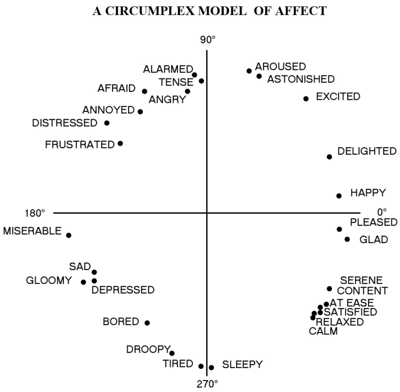
$$P^i \times v = P^i \times v_1 + P^i \times v_2 = {\lambda_1}^i \times v_1 + \overbrace{{\lambda_2}^i \times v_2}^{0(\lambda_2 < 1)}$$
$$= 1^i \times v_1$$
$$= v_1$$

Affect (Emotion): Detection of Affect

Motivation

- Human-computer/human-robot interaction
- Robotics
- Application in user interface design
- Learning environment
- Boredom, Frustration
- Autism spectrum
- Early intervention for stress reduction
- Mental Health Monitoring

Our Approach: Russell's Circumplex Model



Our Approach: Multimodal Algorithm

- Selecting modalities
  - Valence
    - Facial Image
  - Arousal
    - Heart Rate
    - Pupil Size
    - Energy Spent
- Building classifier for each of the modalities
- Evaluate the performance of the single modalities
- Fusing the result of different modalities
- Validate the performance of the multimodal system

Our Approach: Data Collection Tool

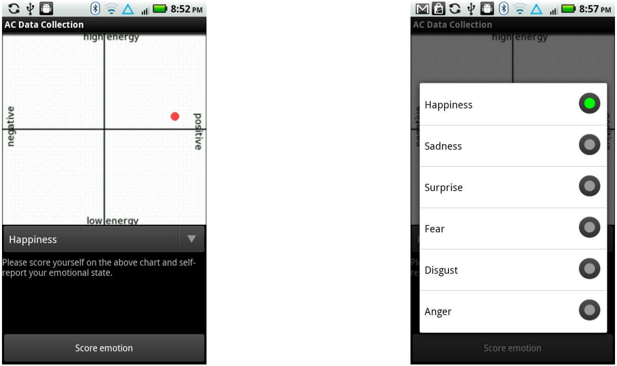


Figure: Annotation of emotion data: (a) Annotation of affective state using Russells 2D emotional space. (b) Annotation of affective state using radio button.

Our Approach: Algorithm

- Facial Image
  - Eigenface method
- Energy Spent
  - Energy $= \int_{t_0}^{t_0+T} |a_x| + |a_y| + |a_z| dt$
- Multimodal Fusion
  - Naïve Bayes Fusion

Results: Unimodal System

a	b	c	d	e	f	←Classified as
8	0	0	0	0	0	| a=happy
0	7	0	0	1	0	| b=anger
1	0	7	0	0	0	| c=sad
1	0	0	7	0	0	| d=disgust
1	0	0	0	7	0	| e=fear
1	0	0	0	0	7	| f=surprise

Table: Confusion matrix for facial expression classifier.

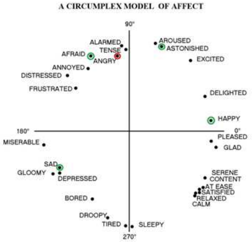
Results: Multimodal System

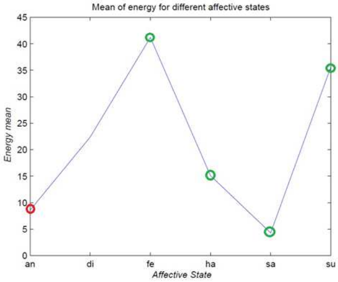
a	b	c	d	e	f	←Classified as
8	0	0	0	0	0	| a=happy
0	8	0	0	0	0	| b=anger
1	0	7	0	0	0	| c=sad
0	0	0	7	0	1	| d=disgust
0	0	0	0	8	0	| e=fear
0	0	0	1	0	7	| f=surprise

Table: Confusion matrix using Naïve Bayes classifier.

Results: Discussion

System performance improved from 89 percent to 93 percent.





Results: Summary

- Multimodal affect detection has better accuracy than uni-modal system.
- Russel's Cirumplex model can be used for designing multimodal system.

Pain Level: Detection of Pain

Motivation

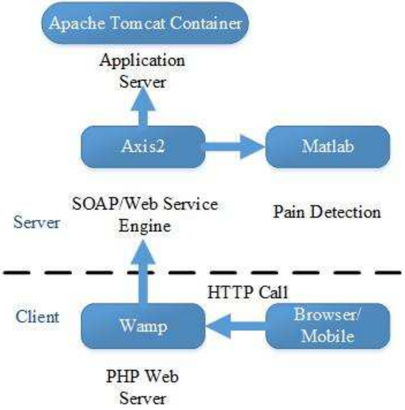
- In excess of 8 million individuals globally die each year from cancer
  - Three-quarters of these are reported to suffer from pain
- A primary barrier for treatment is inadequate information on pain intensity [Grossman, 2004]
- Medication adjustment with pain significantly improves patient outcome [Gawande, 2010]
- Pain assessment is important for
  - Remote monitoring of pain
  - ICU Patients
  - Neonates
  - Verbally impaired patients

Our Approach: Data

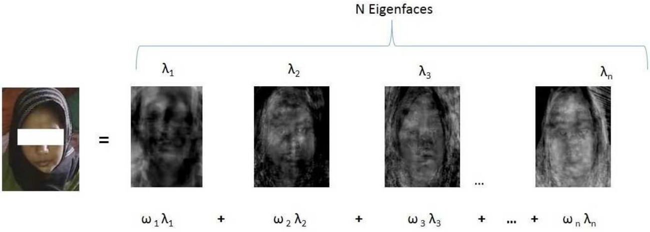
Longitudinal Study			
Subject	Training Set	Test Set	Total
A	6	8	14
B	36	80	116
C	36	124	160
D	6	6	12
E	36	78	114
F	6	32	38
Cross-sectional Study			
Location		Training Set	Test Set
Bangladesh		454	131
Nepal		454	311
United States		454	71

Table: Image data set size for longitudinal and cross sectional study. The entire data set for longitudinal study was used as the training data set for the cross sectional study.

Our Approach: Software Architecture



Eigenvalues and Eigenfaces



Our Approach: Closest Weight Vector of the Image

- Euclidean distance
- Angular distance
- Multi-class support vector machine

Results: First phase–longitudinal study

	Subject B		Subject C		Subject E	
Cross Val	Angular	SVM	Angular	SVM	Angular	SVM
1	0.95	1.07	0.71	0.88	1.06	0.64
2	1.02	1.142	0.71	0.77	1.01	0.67
3	0.79	0.81	0.75	0.80	1.04	0.68
4	1	1.01	0.8	0.78	0.98	0.66
5	1.12	0.97	0.83	0.83	0.98	0.72
6	1.07	0.86	0.707	0.94	1.22	0.66
7	0.88	0.94	0.82	0.87	1.09	0.62
8	0.83	0.91	0.73	0.92	1.12	0.75
9	0.92	0.73	0.78	0.82	1.04	0.53
10	1.04	1.05	0.79	0.78	0.96	0.63
Mean $\pm$SD	0.96 ± 0.10	0.94 ± 0.12	0.76 ± 0.04	0.84 ± 0.06	1.05 ± 0.08	0.66 ± 0.05

Table: Mean absolute error for a 10 fold cross validation for the longitudinal study.

Results: First phase–longitudinal study

	Angular						SVM					
Sub	Sensitivity			Specificity			Sensitivity			Specificity		
	L	M	H	L	M	H	L	M	H	L	M	H
B	0.18	0.91	NaN	0.91	0.18	1	0.18	0.89	NaN	0.89	0.18	1
C	1	0	NaN	0	1	1	0.97	0.04	NaN	0.04	0.97	1
E	0.11	0.88	NaN	0.88	0.21	1	0.24	0.97	NaN	0.97	0.24	1
Mean $\pm$SD	0.43 $\pm$0.45	0.60 $\pm$0.44	NaN	0.60 $\pm$0.44	0.46 $\pm$0.45	1 $\pm$0	0.46 $\pm$0.37	0.60 $\pm$0.43	NaN	0.63 $\pm$0.43	0.46 $\pm$0.37	1 $\pm$ 0

Table: Mean sensitivity and specificity for the longitudinal study. Low(L), Medium(M) and High(H) pain levels are similar to the Brief Pain Inventory (BPI) suggested by World Health Organization (WHO).

Results: Discussion

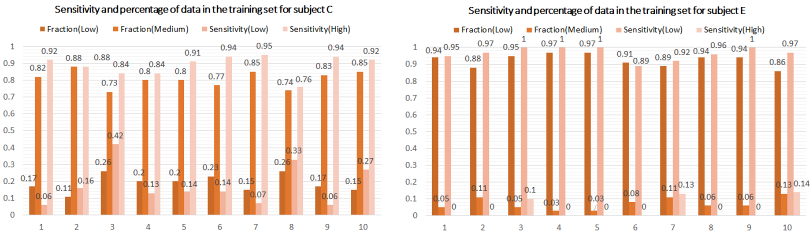


Figure: Fraction of the number of images for the two different classes (low and medium) and the sensitivity for each class for the 10 fold cross validation during the longitudinal study.

Results: Second phase–cross-sectional study

Angular						SVM					
Sensitivity			Specificity			Sensitivity			Specificity		
L	M	H	L	M	H	L	M	H	L	M	H
0.55	0.39	0.02	0.40	0.58	0.99	0	1	0	1	0	1

Table: Sensitivity and specificity for the cross-sectional study when the entire data set from the longitudinal study was used as the training data set.

Results: Summary

- A personalized model works better for pain detection.
- The training data should represent the application scenario.
- Low, medium and high pain levels: similar to Brief Pain Inventory (BPI) and possible for clinical application.

Arterial Blood Pressure: Identification of Early Markers of Hemorrhage

Motivation

- Hemorrhage is the cause of 40% of deaths after a traumatic injury in the United States [Kauvar, 2006].
- One of the limitations to treating hemorrhage
  - Vital signs can appear normal until a significant blood loss has occurred.
- In a mass casualty situation
  - Identifying patients that need immediate care.
- In a combat situation
  - Risks the life of the paramedics.
- Existing algorithms that use mean arterial pressure or heart rate variability has limitations such as:
  - Mean arterial pressure does not change due to the compensating mechanism until at a later stage.
  - Heart rate variability changes may depend on individual responses.

Our Approach: Data

- This project is supported by the Medical Countermeasures Initiative (MCMi) and by an appointment to the Research Participation Program at the Center for Devices and Radiological Health administered by the Oak Ridge Institute for Science and Education through and interagency agreement between the U.S. Department of Energy and the U.S. Food and Drug administration.
- Data is provided by slow hemorrhage of pigs from the University of Texas Medical Branch at Galveston (UTMB).

Our Approach: Algorithm

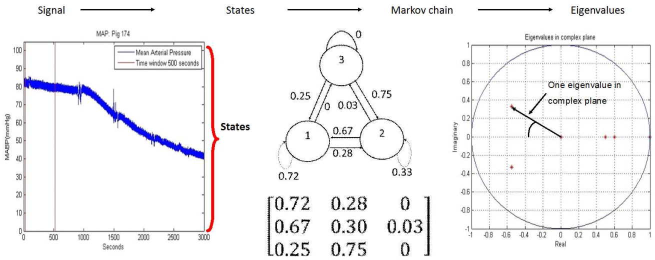
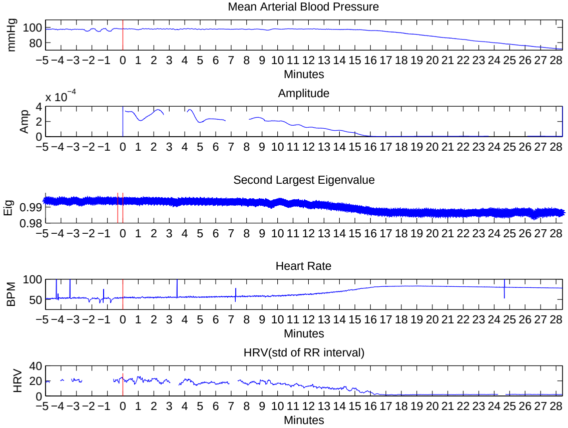


Figure: (a) Mean Arterial Pressure of a pig. (b) A sample Markov Chain Model with the transition probabilities and the corresponding matrix. (c) Eigenvalues of a transition probability matrix in complex plane with angle and absolute value.

Results: Case Study– Pig 515

- One hemorrhage
  - 6.3 mL/min or 0.3 mL/min/kg
  - Weight 21 kg
  - First and only hemorrhage: total time 29 minutes

Results: Change of Signals for Pig 515



Results: Correlation coefficient

Animal	Heart Rate	Systolic Blood Pressure	Pulse Pressure	Shock Index
A	-0.10	0.47	0.56	-0.59
B	-0.99	0.94	0.98	-0.93
C	-0.09	0.96	0.93	-0.95
D	-0.99	0.98	0.93	-0.98
E	0.36	0.78	-0.31	- 0.82
F	-0.76	0.97	0.96	-0.98
G	-0.98	-0.66	-0.95	- 0.97
Group Statistics				
Median	-0.76	0.94	0.93	-0.95
Min	-0.99	-0.66	-0.95	-0.98
Max	0.36	0.98	0.98	-0.59

Table: Correlation coefficients between mixing rate and vital signs during hemorrhage. Shock index is systolic blood pressure divided by heart rate.

Results: Summary

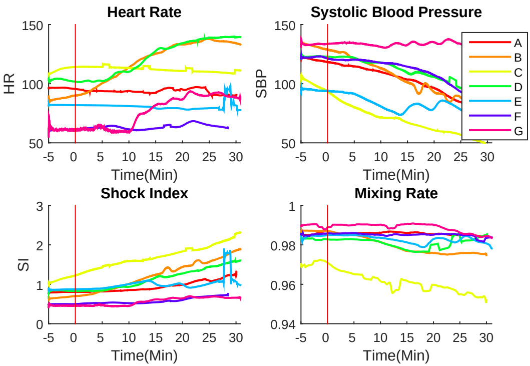


Figure: The vital signs (heart rate, systolic blood pressure, and shock index) for each animal along with the mixing rate during hemorrhage.

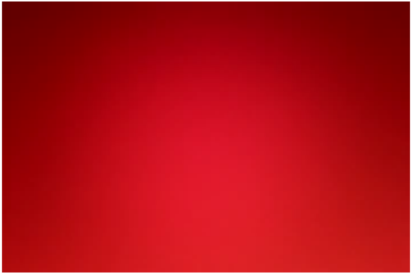
Results: Summary

- The mixing rate of the Markov chain is strongly correlated with shock index.
- The exact reason for the change in the mixing rate might be due to the morphological change in the arterial blood pressure due to hemorrhage and needs to be investigated.
- It has the potential to be used in clinical setting for detecting hemorrhage or predicting shock.

Hemoglobin Level: Assessment of Hemoglobin From Mini-video Image

- Is an important vital sign for multiple medical conditions including sickle cell disease (SCD).
- The estimated cost of care for people with sickle cell disease in the United States is 1.1 Billion dollars.
- Per-patient rate of admission to the ED and hospital is 6 times per year.
- Accurate hemoglobin level detection can reduce number of hospital admission.

Our Approach: Finger-tip Video



Our Approach: Noninvasive Hemoglobin Level

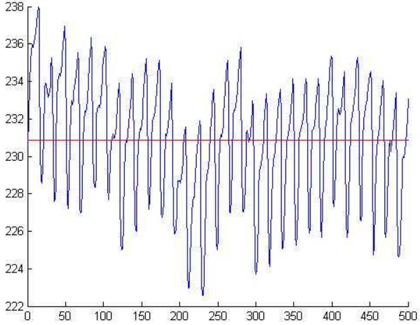


Figure: We propose to use a calibration table for blood hemoglobin level and pixel intensity

Our Approach: Data

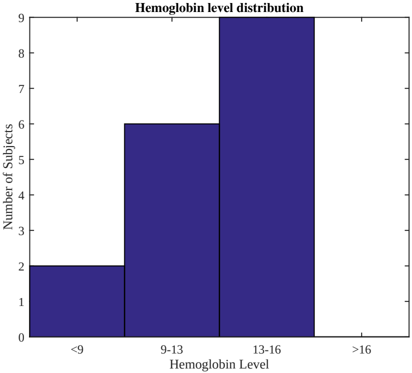


Figure: Distribution Of Hemoglobin Level

Results: Distribution of Hemoglobin Level

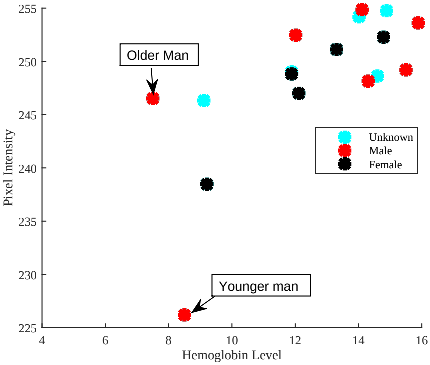


Figure: Hemoglobin Level And Red Pixel Intensity

Results: Proposed Model

- Research Hypothesis (1)
  - The red pixel intensity of finger tip video image is positively correlated with hemoglobin level.
- Research Hypothesis (2)
  - The red pixel intensity of finger tip video is positively correlated with oxygenation.
- Research Hypothesis (3)
  - The red pixel intensity of finger tip video is negatively correlated with skin thickness.

$$RPI = \beta_0 Hem + \beta_1 Oxy + \beta_2 ST + \epsilon$$

Where

- RPI =Red Pixel Intensity
- Hem =Hemoglobin Level
- Oxy =Oxygenation
- ST =Skin Thickness
- ϵ = Error

Results: Summary

- Hemoglobin level might be correlated with red pixel intensity.
- A large pilot study is needed.
- Work in progress with Blood Center of Wisconsin and Medical College of Wisconsin.

Evaluation: Evaluation of Machine Learning Algorithms for Clinical Application.

Motivation

- Algorithm development is not enough.
- Performance evaluation of these algorithms are critical to provide warnings with high sensitivity and reduced numbers of false alarms to address alarm fatigue for clinical application.
- We investigated early warning systems for evaluation.
- Early warning systems include algorithms that use multiple vital signs to monitor patients and recognize early deterioration.
- The aim of this research is to investigate how algorithm development techniques (selection of training, testing and validation data set) can affect performance using a publicly available data set.

Motivation

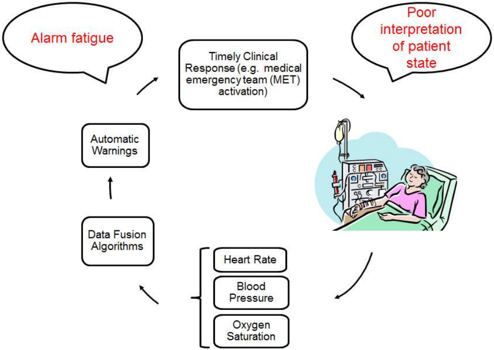


Figure: Motivation

Our Approach: Data

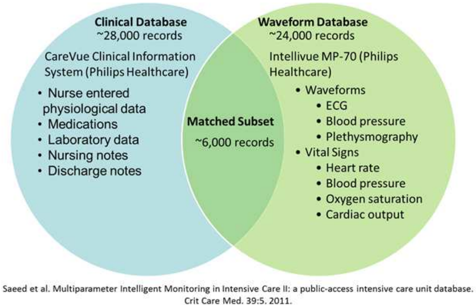


Figure: Multi-parameter Intelligent Monitoring In Intensive Care Database

Our Approach: Selection of Training, Testing and Validation Data Set

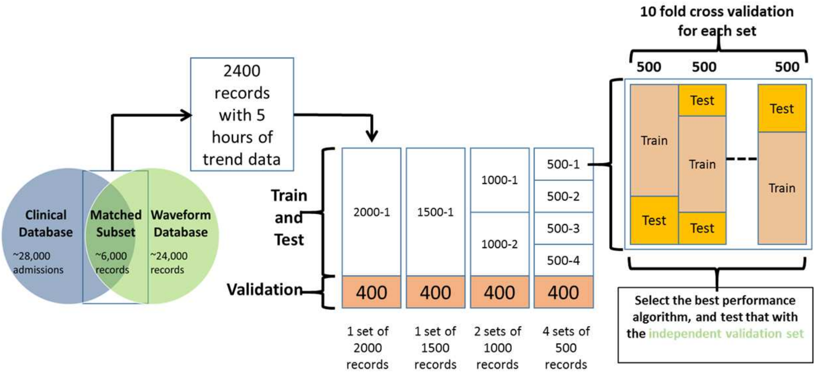


Figure: Training, Testing and Validation Data Set

Our Approach: Observation, Gap and Target Window

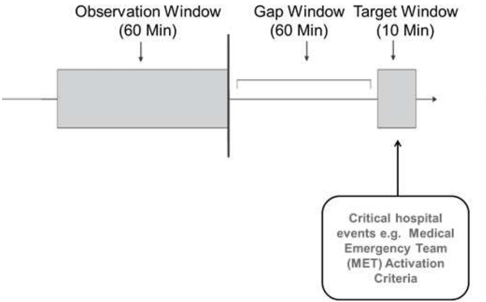


Figure: Observation, Gap and Target Window

Our Approach: Algorithms

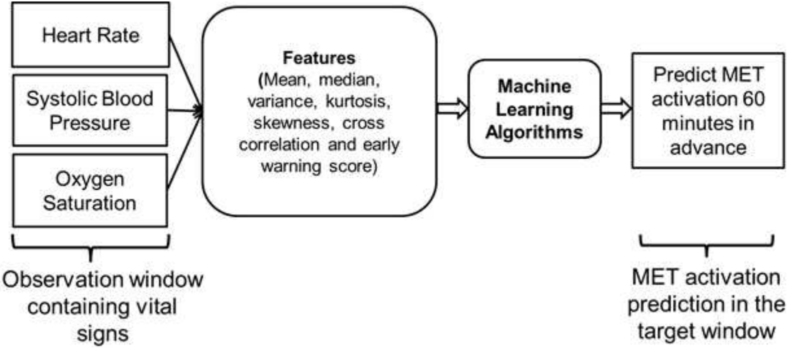
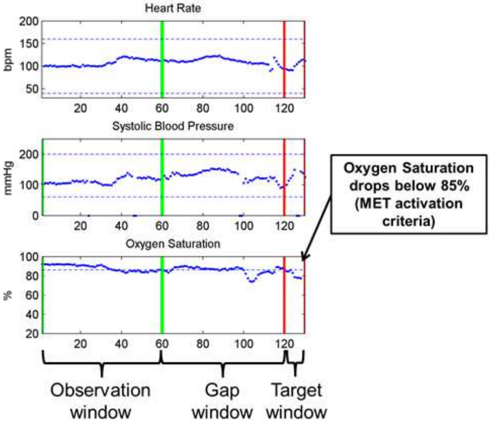
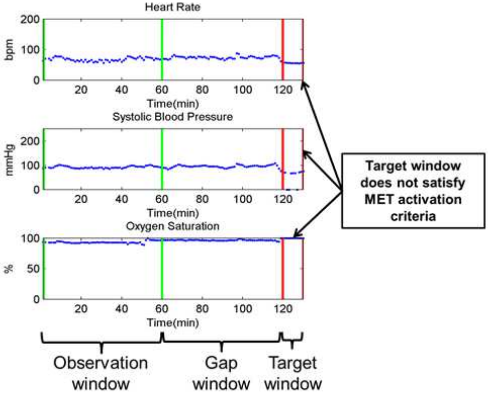


Figure: Feature Selection

Our Approach: Medical Emergency Team Activation (MET)– True Positive



Our Approach: Medical Emergence Team Activation (MET)– True Negative



Our Approach: Decision Tree

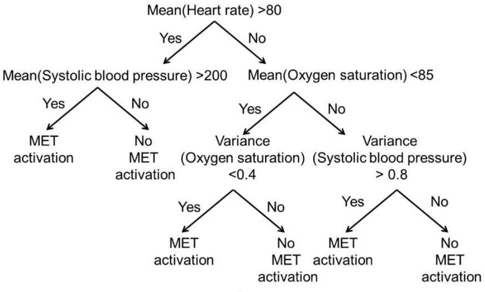


Figure: Example of a decision tree for MET activation

Our Approach: Support Vector Machine

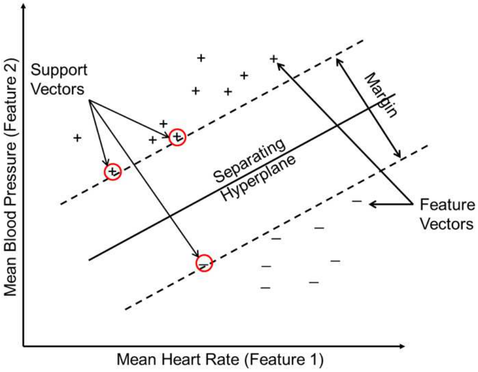


Figure: Support Vector Machine

Our Approach: National Early Warning Score

PHYSIOLOGICAL PARAMETER	3	2	1	0	1	2	3
Respiration Rate	≤8		9-11	12-20		21-24	≥25
Oxygen Saturation	≤91	92-93	94-95	≥96			
Systolic BP	≤90	91-100	101-110	111-219			≥220
Heart Rate	≤40		41-50	51-90	91-110	111-130	≥131

Figure: Thresholds for different vital signs for different score using NEWS.

- True positive using NEWS:
  - If any of the vital signs reaches the threshold of 3 for 10 minutes.
  - If the cumulative score reaches 5 for 10 minutes.

Results: Sensitivity

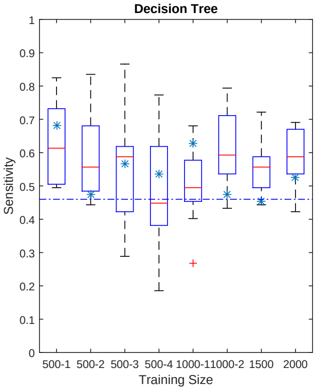


Figure: Sensitivity for different approaches.

Results: Specificity

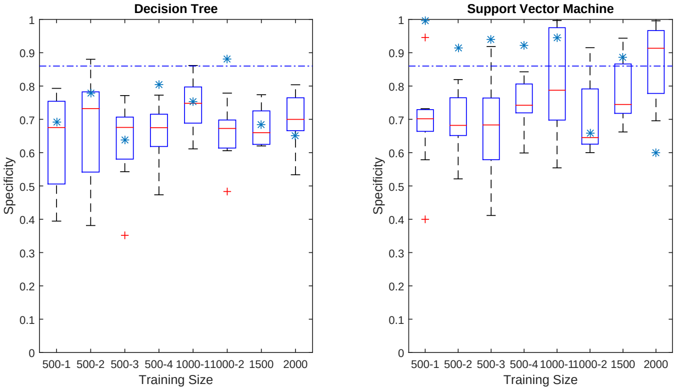


Figure: Specificity for different approaches.

Results: Area Under The Curve

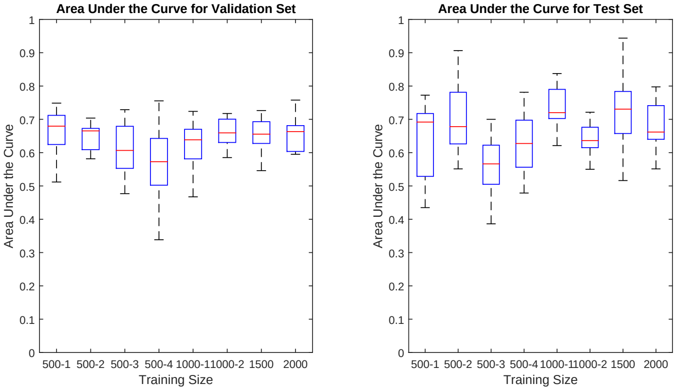


Figure: Area under the curve (AUC) for decision tree.

Results: Summary

- With a fixed training set, there is much variability in the performance of the algorithms depending on the random split for training and testing.
- Increasing the number of records in the training set did not necessarily increase algorithm sensitivity.
- The 'best' algorithm using the test sets is not necessarily the best algorithm for an 'independent validation set'.
- Future work to improve early warning patient monitoring algorithms should investigate:
  - Key signal features to include in the algorithms.
  - Alternative techniques to combine information from multiple sources.

Conclusion: Summary

- Motivation
- Background
- Detection of Affect, RACS 2013 (Best Paper Award)
- Detection of Pain, COMPSAC 2015
- Blood Pressure (Identification of Early Markers of Hemorrhage), (EMBC 2014)
- Hemoglobin Level, Collaboration with Blood Center of Wisconsin
- Evaluation for Application in Clinical Setting, Collaboration with the FDA
- Conclusion

Conclusion: Acknowledgment

- Sheikh Iqbal Ahamed, Advisor and Director, Ubicomp Lab, Marquette University
- Stephen Merrill, Advisor and Graduate Chair, Marquette University
- Dennis Brylow, Associate Professor, Marquette University
- Praveen Madiraju, Associate Professor, Marquette University
- Bhagwant Sindhu, Assistant Professor, UWM
- Richard Love, Director, IBCRF
- Munir Haque, Research Scientist, RCHE, Purdue University
- David Strauss, Medical Officer, US FDA
- Christopher Scully, Post-doctoral Scientist, US FDA
- Joshua Field, Associate Professor, Medical College of Wisconsin
- Richard Povinelli, Associate Professor, Marquette University

Conclusion: Publications

Journal Papers

- Md Munirul Haque, Ferdaus Ahmed Kawsar, **Mohammad Adibuzzaman**, Md. Miftah Uddin, Sheikh Iqbal Ahamed, Richard Love, Ragib Hasan, Rumana Dowla, Tahmina Ferdousy, Reza Salim:**e-ESAS: Evolution of a participatory design-based solution for breast cancer (BC) patients in rural Bangladesh** in Personal and Ubiquitous Computing, 19(2): 395-413 (2015)
- **Mohammad Adibuzzaman**, Niharika Jain, Nicholas Steinhafel, Munirul Haque, Ferdaus Ahmed, Sheikh Ahamed, Richard Love: **In-situ Affect Detection in Mobile Devices: A Multimodal Approach for Advertisement Using Social Network** in ACM SIGAPP Applied Computing Review,13(4): 67-77 (2013)

Conference/Workshop Papers

- **Mohammad Adibuzzaman**, Colin Ostberg et al.: **Assessment of Pain Using a Smart Phone** submitted to COMPSAC 2015
- **Mohammad Adibuzzaman**, George C. Kramer, Loriano Galeotti et al.: **The Mixing Rate of the Arterial Blood Pressure Waveform Markov Chain is Correlated with Shock Index During Hemorrhage in Anesthetized Swine** in Proceedings of EMBC 2014, Chicago, USA
- **Mohammad Adibuzzaman**, Sheikh Ahamed et al.: **A Personalized Model for Monitoring Vital Signs using Camera of the Smart Phones** in Proceedings of SAC 2014,444-449, Seoul, Korea
- Md Munirul Haque, Ferdaus Kawsar, **Mohammad Adibuzzaman**, Mohammad Miftah Uddin, Sheikh Iqbal Ahamed et al.: **Barriers for Breast Cancer (BC) Patients in Rural Bangladesh: Design and Deployment of a Mobile based Solution** in Proceedings of the 20th Americas Conference on Information Systems (AMCIS 2014), August 7-10, Savannah, Georgia.
- Md Haque, **Mohammad Adibuzzaman**, Md Uddin, Ferdaus Kawser, Sheikh Ahamed, Richard Love, et al.: **Findings of Mobile based Palliative Care System: Towards a Generic Framework for Measuring QoL** in Proceedings of PervasiveHealth 2014, 1-8, Oldenburg, Germany

Publications

- **Mohammad Adibuzzaman**, Niharika Jain et al.: **Towards In Situ Affect Detection in Mobile Devices: A Multimodal Approach** in Proceedings of RACS 2013 (Best paper award), Montreal, Canada
- Md Munirul Haque, **Mohammad Adibuzzaman** et al.: **Findings of e-ESAS: A Mobile Based Symptom Monitoring System for Breast Cancer Patients in Rural Bangladesh** in Proceedings of CHI 2012(Nominated for best paper award), 899-908, Austin, USA
- Ferdaus Kawsar, Munirul Haque, **Mohammad Adibuzzaman**, Sheikh Iqbal Ahamed, et al.: **e-ESAS: Improving Quality of Life for Breast Cancer Patients in Developing Countries** in Mobile Health 2012, SC, USA, 2012.
- Munirul M Haque, Ferdaus Kawsar , **Md. Adibuzzaman**, Sheikh I. Ahamed et al.: **Mobile Based health Care Solution for Breast Cancer Patients** in M4D 2012, New Delhi, India
- Md. Munirul Haque, **Md Adibuzzaman** et al. **IRENE: Context Aware Mood Sharing for Social Network** in KASTLES 2011 Workshop, Irvine, USA
- Chowdhury Sharif Hasan,**Mohammad Adibuzzaman**, Ferdaus Ahmed Kawsar, Munirul M. Haque, Sheikh Iqbal Ahamed: **PryGuard: A Secure Distributed Authentication Protocol for Pervasive Computing Environment** IEA/AIE (1) 2011: 135-145

Posters

- **Mohammad Adibuzzaman**, David G. Strauss, Stephen Merrill, Loriano Galeotti, Christopher Scully: **Evaluation of Machine Learning Algorithms for Multi-parameter Patient Monitoring** in Student Poster Competition at the US FDA, 2014

Publications

- **Mohammad Adibuzzaman**, Loriano Galeotti et al.: **A Novel Index to Monitor Physiological Systems from the Arterial Blood Pressure Waveform during Hemorrhage** in MCMi Regulatory Science Symposium, 2014, Maryland, USA
- **Mohammad Adibuzzaman**, Loriano Galeotti et al.: **Markov chain methods in identifying early acute hypotensive episodes** in MCMi Regulatory Science Symposium, 2013, Maryland, USA
- Munirul Haque, Sheikh Iqbal Ahamed, Rumana Dowla, Ferdaus Kawsar, **Mohammad Adibuzzaman** et al.: **Design and Deployment of e-ESAS: A mobile based symptom monitoring system for Breast cancer patients in Rural Bangladesh** in Proceedings of 34th Great Lake Biomedical Conference, Milwaukee, WI, USA. April, 2012.
- Md Munirul Haque, Ferdaus Kawsar, **Mohammad Adibuzzaman**: **Findings from the Deployment of e-ESAS: A Remote Symptom Monitoring System for Rural Breast Cancer Patients in Bangladesh** in Proceedings of the Forward Thinking Poster Session/Colloquy Presentation, Marquette University, December 2011 .
- **Mohammad Adibuzzaman**, Feredaus Ahamed Kawsar, Md Munirul Haque, Md Osman Gani, Nicholas Steinhafel: **Multimodal Ubiquitous Affect Detection for Social Network** in Proceedings of the Forward Thinking Poster Session/Colloquy Presentation, Marquette University, December 2011 .

Extra Slides

Heart Rate, Oxygen Saturation and Perfusion Index

Motivation

- Smart phones with optical sensors have created new opportunities for low cost and remote monitoring of vital signs.
- We propose to find vital signs from the video image captured by a smart phone with the flash light of the camera on.

Our Approach: Time series data

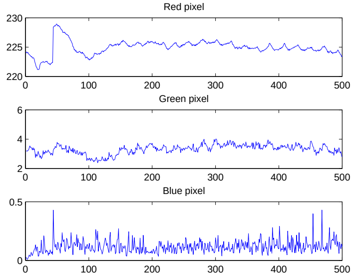


Figure: Red, Green and Blue component varying from frame to frame. The horizontal axes represent number of frame and vertical axes represent pixel value (between 0 and 255)

Our Approach: Heart Rate

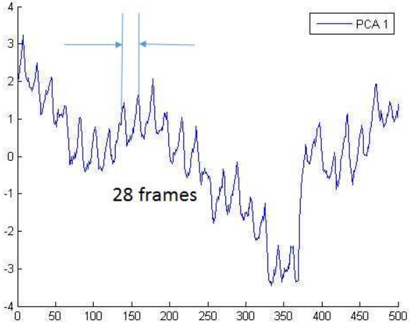


Figure: Heart rate can be calculated using the formula
$$HR = \frac{FrameRate * 60}{NumberOfFramesBetweenTwoPeaks}$$

Our Approach: Perfusion Index

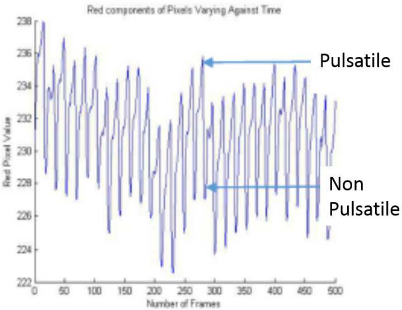


Figure: Proposed approach for perfusion index which is defined as the pulse strength

Our Approach: Oxygen Saturation

$$SpO2 = \frac{HbO2}{HbO2+Hb}$$

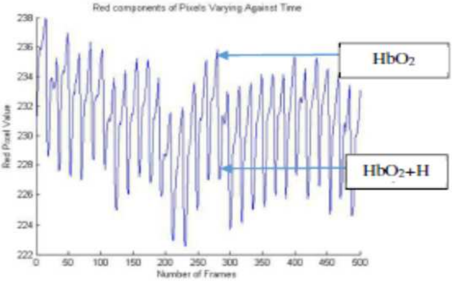
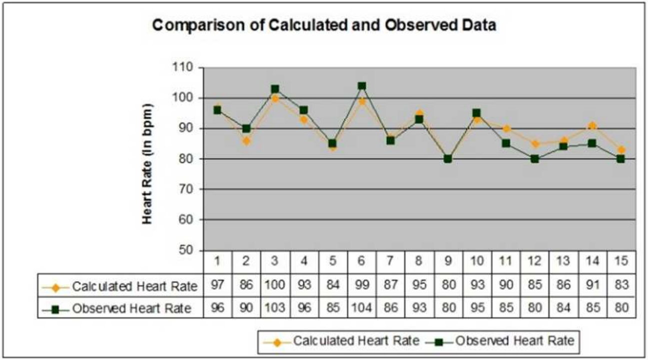


Figure: Proposed approach for oxygen saturation which is defined as the ration between oxygenated hemoglobin and total hemoglobin.

Results: Heart Rate



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Calculated Heart Rate	97	86	100	93	84	99	87	95	80	93	90	85	86	91	83
Observed Heart Rate	96	90	103	96	85	104	86	93	80	95	85	80	84	85	80

Figure: Comparison of Results With Our approach and Pulse Oximeter.

Results: Regression Model for Perfusion Index

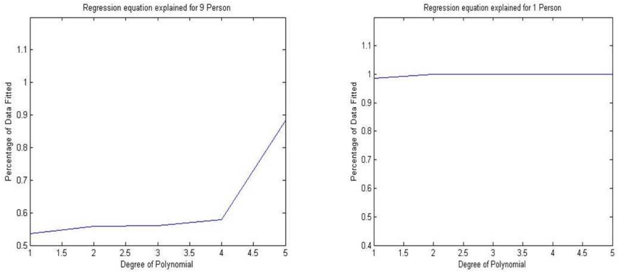
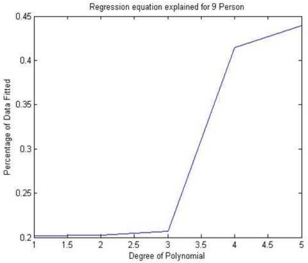


Figure: It takes a polynomial of degree 5 for polynomial fit of perfusion index for 9 persons with ninety percent data fit. b) Only a linear equation explains ninety percent data for one person.

Results: Regression Model for Oxygen Saturation



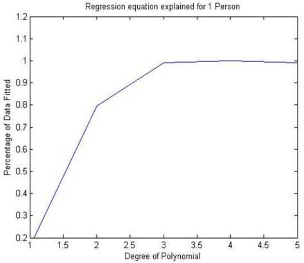


Figure: a) It takes a polynomial of degree 5 for peripheral oxygen saturation for 9 persons with only forty three percent data fit. b) Only a quadratic equation explains eighty percent data for one person.

Results: Summary

- Heart rate can be calculated from video images with high accuracy.
- A personalized model for oxygen saturation and perfusion index can be developed with good accuracy.
- A validation study is needed for clinical application.

Eigenvalues Contd.

- This is the basis for the algorithms used for smart monitoring of health parameters.
- Principal component analysis and mixing rate of Markov chain both are based on this very interesting property.

Mixing Rate or Second Largest Value of Markov Chain

- The largest eigenvalue of a Markov transition matrix is 1.
- The second largest eigenvalue of the matrix determines how fast the chain would converge to the limit distribution.
- The second largest eigenvalue is called the mixing rate of the Markov chain.

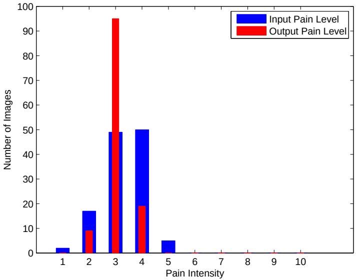
Naïve Bayes Fusion

Given a problem with K classes and C different classifiers, λ_i, $i = 1, ..., C$ we like to infer the true class label ω, given the observation x. Assuming that for each classifier λ_i we have a predicted class label ω_k, where $k = 1, ..., K$ then the true class label can be derived as follows:

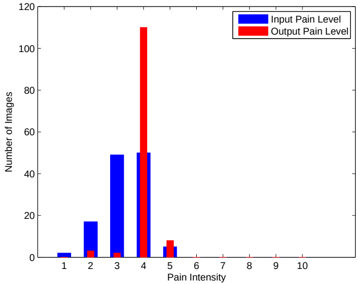
$$P(\omega|x) \approx P(\omega|\omega_k, \lambda_i)P(\omega_k|\lambda_i, x)P(\lambda_i|x)$$

Probabilities $P(\omega|\omega_k, \lambda_i$ and $P(\lambda_i|x)$ are used to weight the combined decision and can be approximated from the confusion matrix of classifier λ_i.

Input and Output Pain Level Distribution: Subject 3



(a) Input and output pain level distribution using SVM



(b) Input and output pain level distribution using SVM

Figure: Input and output pain level distribution

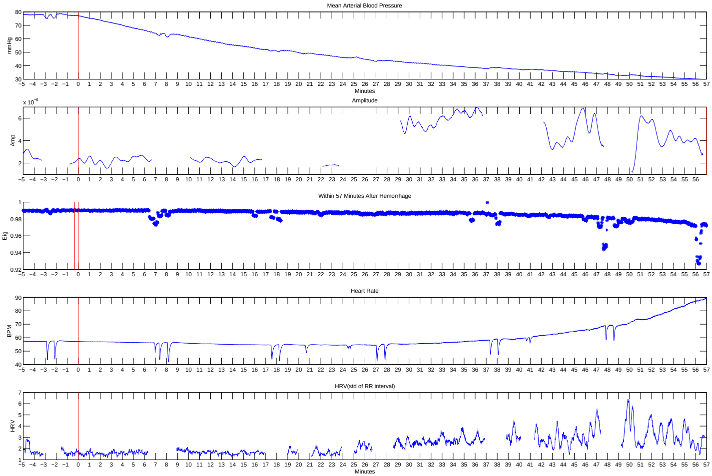
Testing

- New Image is projected on the Eigenspace
- A new weight vector is calculated
- Closest weight vector is found from the training image
- The pain label of the training image corresponding to the weight vector is returned

Case Study 3: Pig 174

- One hemorrhage
  - 17.8 mL/min equivalent to 0.3 mL/min/kg
  - Weight 59.3 kg
  - Hemorrhage is started around an hour after Protocol 1
  - Protocol 1 of this experiment is done to evaluate the effect of vasoconstrictors (Phenylephrine, PHP)
  - Nexfin data (such as noninvasive blood pressure) are present
  - First and only hemorrhage: total time 57 minutes

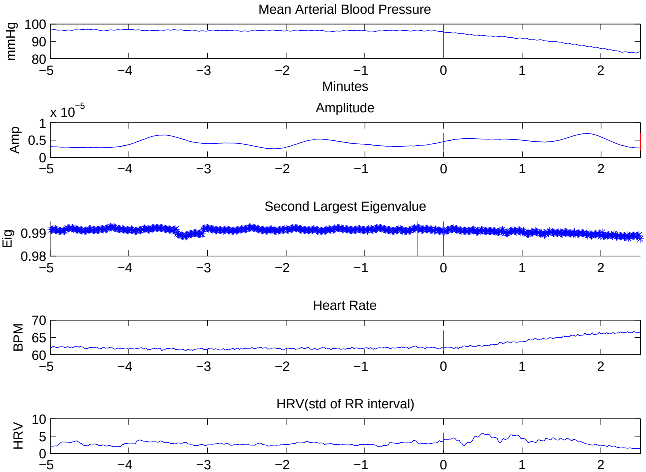
Change of Signals for the Pig 174



Case Study 4: Pig 404

- Seven different hemorrhages
  - Protocol 1
    - 60 mL/min equivalent to 2 mL/min/kg (4 hemorrhages)
    - 30 mL/min equivalent to 1 mL/min/kg
    - 10 mL/min equivalent to 0.3 mL/min/kg
  - Hemorrhage to death
    - 3 mL/min equivalent to 0.1 mL/min/kg
  - Weight 30 kg
  - Protocol 1 of this experiment is done to evaluate the effect of Hextend bolus on various types of hemorrhages
  - All the hemorrhages except the last one is part of protocol one
  - The last hemorrhage is a 5 hour long hemorrhage
  - First hemorrhage: total time 2.5 minutes

Change of Signals for the Pig 404



Eigenvalues of Markov Chain: Example Continued

For the previous transition matrix, the normalized eigenvector corresponding to 1 is,

$$\pi = \begin{bmatrix} 0.7014 \\ 0.2899 \\ 0.0087 \end{bmatrix}$$

In our case

$$P^{100} = \begin{bmatrix} 0.7014 & 0.7014 & 0.7014 \\ 0.2899 & 0.2899 & 0.2899 \\ 0.0087 & 0.0087 & 0.0087 \end{bmatrix}$$

Each column of the probability distribution becomes the eigenvector normalized.

Research to Identify Facial Expression

- Facial Action Coding System [Ekman, 2002]
- Image processing techniques using machine learning

Case Study 2: Pig 517

- 5 different hemorrhages
  - 21 mL/min or 1 mL/min/kg
  - Weight 21 kg
  - The last 4 hemorrhages use closed loop fluid control
  - First hemorrhage: total time 9.5 minutes

Change of Signals for the Pig 517