**Human Performance Recognition**

**Needs Statement:**

Traditionally, live military exercises involving operations in urban terrain have relied heavily on the use of multiple instructor observers moving behind, beside, or above small units in training. Modernized live fire training ranges have undergone extensive instrumentation including Closed Circuit Television and long-range night vision camera systems to provide safer and more thorough observation. While camera technology has increased in resolution and affordability, the reliance on instructor observers (human) processing multiple camera feeds into a single After Action Review (AAR) capability continues to be time consuming, and inconsistent (relying on individual instructor experience/knowledge).

With an increasing concern on affordability of range operations and cost to maintain infrastructure, a need has risen to evaluate the potential value of utilizing machine learning to automatically (and more consistently) identify human performance. Initial studies have already been made into the use of video analytics which to date have not satisfied all the operational requirements. As a result, an investigation has been requested into the use of human tracking and individual biometric sensor technologies which may provide individual and small unit level data streams, processed in real time by trained ML models.

The anticipated result would be reliable recognition of basic human activity (include positional movement and biometric recordings if possible). There is also uncertainty regarding the relative effect of variance in the sensor characteristics. Therefore, it is anticipated that the study will either evaluate, or account for the use of different sensor technologies. A conclusion should be made as to which sensor technologies provide the best recognition of human activity, using the same trained model.

Results shall be visualized in a way that provides a graphic representation of human activity based on different data sets and sensors, including the resultant classification of activity made by the trained model. Results shall include a distribution or categorization of at least two types of human subjects which compares an attribute of their performance (i.e. speed, endurance). This may require measurement of comparative heart rate to run rate, or distance over time, where the data supports the analysis.

Based on reliable data sets, provide a simulation of one or more soldiers (of different types), performing a specific drill or exercise, and demonstrate how accurately the trained model recognizes the human activity, and if possible, compare the relative performance of the soldiers.

**Approach:**

**Part 1:**

Select one or more of the following UCI datasets to train human activity recognition models. -> Selected the PAMAP2 dataset.

Examine the dataset with Jupyter Notebook. Examine the quality of the data and make observations regarding the scope of the data set and its suitability for the project objectives. -> Removed activities that do not directly relate to soldier activity. Use the following activities as a substitution for the recorded activities to make relevant to soldier activities;

soldieractivity\_id = {

0: 'transient', 1:'lying', 2:'sitting', 3:'standing',

4:'walking', 5:'running', 7:'hiking',

10:'operating C2', 11:'operating vehicle',

12:'ascending stairs', 13:'descending stairs'}

Divide the data sets into Train and Test, and store these as CSV files.

Using Sklearn, train models and compare the prediction accuracy of Decision Tree and SVN methods.

Compare the performance of the trained models on a normalized data set that utilizes the most essential attributes for basic activity recognition. Make observations regarding the techniques used to train the models, and identify the key parameters modified to achieve the most optimum result. Try to identify any factors in the data or techniques that constrain the performance of the model in successfully recognizing human activity. Which activities are the easiest to recognize, and which activities are the most difficult. Consider what aspects of the sensors (characteristics, number, location) might be the most important factors for successful recognition. Compare chest and ankle sensors.

**Part 2:**

Analyze the data set to determine the expected range of individual human performances. Categorize the data by performance category (i.e. easy / moderate / hard or slow / moderate / fast). This will likely require more processing, based on the gate length calculated by the subject height ratio. A step frequency counter will also be required to determine land speed, assuming the recorded subject is actually walking or running (rather than on the spot). Select at least two types or categories of human activity and attempt to train the model to recognize the difference in performance (i.e. fast/slow run). **May need to leave this portion out given time constraints.**

Build a mock scenario of two or more participants of different type / category, and visually demonstrate the use of the Human Performance Recognition capability. Document any observations and challenges made during the final demonstration. Build a flask-based API that publishes two or more sensor data streams to the model (one stream per participant / subject id) and provide a visual representation of the human activity with recognition results in real time. Based on the separation of 4 subjects, and filtering down the number of activities to 12 (1:'lying', 2:'sitting', 3:'standing', 4:'walking', 5:'running', 7:'Nordic walking', 12:'ascending stairs', 13:'descending stairs',

19:'house cleaning', 24:'rope jumping); it is clear that the ‘sim\_data’ sets include a total duration of 60-70 minutes of activities per subject. Therefore, we need to break out the individual activities per ‘sim\_data’ set. Break into only four activities across two subjects for the initial flask API, where at least one of each activity intensity type (low, medium, heavy) is included. Visualize the data in Tableau and make observations. High thermal visibility is observed over walking activity versus running (possibly due to windage).

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub1_AvgHRbyActivity/Sub1_AvgHRbyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub2_AvgHRbyActivity/Sub2_AvgHRbyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub5_AvgHRbyActivity/Sub5_AvgHRbyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub8_AvgHRbyActivity/Sub8_AvgHRbyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub1_AccelRangebyActivity/Sub1_AccelRangebyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub2_AccelRangebyActivity/Sub2_AccelRangebyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub5_AccelRangebyActivity/Sub5_AccelRangebyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub8_AccelRangebyActivity/Sub8_AccelRangebyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub1_GyroRangebyActivity/Sub1_GyroRangebyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub2_GyroRangebyActivity/Sub2_GyroRangebyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub5_GyroRangebyActivity/Sub5_GyroRangebyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub8_GyroRangebyActivity/Sub8_GyroRangebyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub1_MagRangebyActivity/Sub1_MagRangebyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub2_MagRangebyActivity/Sub2_MagRangebyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub5_MagRangebyActivity/Sub5_MagRangebyActivity?publish=yes>

<https://public.tableau.com/profile/robbie.phillips#!/vizhome/Sub8_MagRangebyActivity/Sub8_MagRangebyActivity?publish=yes>

Some further analysis could include any correlation with the height and BMI of each subject wrt physical performance.

Notes: Start with a quick end to end of the project, based upon previous research, then with available time, deepen the analysis and ML investigation. Consider a future state as the focus of the challenge. How will the models perform on a smaller processing footprint. If a normalized data set is not achievable, consider training a model for each data set with unique sensor/locations and compare them. Then try to predict what the best sensor technology and placement would provide the best results, and then adapt the model to do more (predict human performance based on heart rate data). Consider DASK running three time-phased models in 2.56/2 oversample and resolve in real time to see if model accuracy improves during run time of data streams.

PAMAP2 appears to be the highest utilized dataset for research on human activity, sampled at 100Hz.

WESAD appears to more directly address heart rate and stress, sampled at 700Hz.

<https://www.zamzar.com/uploadComplete.php?convertFile=mp4&to=gif&session=ea51a2485483d0ac3589e42dd2d4cf&email=false&tcs=Z85>

Former Research:

Discussion & Future Work ● The dataset provides input features that likely would not be present in real-world applications, like chest and ankle IMUs. We found we could get relatively good performance using just hand IMU and heart rate, the type of data one might get from a smart watch. ● Logistic regression unsurprisingly performed the worst as it is a linear classifier. ● As expected, ensembling (random forest and boosting) improved test accuracy over the original decision trees. ● The neural net consistently provided high accuracies at the cost of long train times and relatively slow classification. In the future we would try using RNNs to classify more complex tasks that depend on sequential lower level actions. ● In the future we would like to test these models using real IMU’s. In particular, we would want to see if a low-compute embedded device could perform classifications with NN’s or SVM’s in real time, in addition to computationally cheaper decision trees.

**UCI Datasets:**

Set 3:

<http://archive.ics.uci.edu/ml/datasets/pamap2+physical+activity+monitoring>

|  |  |
| --- | --- |
| **Abstract**: The PAMAP2 Physical Activity Monitoring dataset contains data of 18 different physical activities, performed by 9 subjects wearing 3 inertial measurement units and a heart rate monitor. |  |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Data Set Characteristics:** | Multivariate, Time-Series | **Number of Instances:** | 3850505 | **Area:** | Computer |
| **Attribute Characteristics:** | Real | **Number of Attributes:** | 52 | **Date Donated** | 2012-08-06 |
| **Associated Tasks:** | Classification | **Missing Values?** | Yes | **Number of Web Hits:** | 78253 |

**Source:**

Attila Reiss, Department Augmented Vision, DFKI, Germany, attila.reiss '@' dfki.de   
Date: August 2012.

**Data Set Information:**

The PAMAP2 Physical Activity Monitoring dataset contains data of 18 different physical activities (such as walking, cycling, playing soccer, etc.), performed by 9 subjects wearing 3 inertial measurement units and a heart rate monitor. The dataset can be used for activity recognition and intensity estimation, while developing and applying algorithms of data processing, segmentation, feature extraction and classification.   
  
\*\* Sensors \*\*   
3 Colibri wireless inertial measurement units (IMU):   
- sampling frequency: 100Hz   
- position of the sensors:   
- 1 IMU over the wrist on the dominant arm   
- 1 IMU on the chest   
- 1 IMU on the dominant side's ankle   
HR-monitor:   
- sampling frequency: ~9Hz   
  
\*\* Data collection protocol \*\*   
Each of the subjects had to follow a protocol, containing 12 different activities. The folder â€œProtocolâ€ contains these recordings by subject.   
Furthermore, some of the subjects also performed a few optional activities. The folder â€œOptionalâ€ contains these recordings by subject.   
  
\*\* Data files \*\*   
Raw sensory data can be found in space-separated text-files (.dat), 1 data file per subject per session (protocol or optional). Missing values are indicated with NaN. One line in the data files correspond to one timestamped and labeled instance of sensory data. The data files contain 54 columns: each line consists of a timestamp, an activity label (the ground truth) and 52 attributes of raw sensory data.

**Attribute Information:**

The 54 columns in the data files are organized as follows:   
1. timestamp (s)   
2. activityID (see below for the mapping to the activities)   
3. heart rate (bpm)   
4-20. IMU hand   
21-37. IMU chest   
38-54. IMU ankle   
  
The IMU sensory data contains the following columns:   
1. temperature (Â°C)   
2-4. 3D-acceleration data (ms-2), scale: Â±16g, resolution: 13-bit   
5-7. 3D-acceleration data (ms-2), scale: Â±6g, resolution: 13-bit   
8-10. 3D-gyroscope data (rad/s)   
11-13. 3D-magnetometer data (Î¼T)   
14-17. orientation (invalid in this data collection)   
  
List of activityIDs and corresponding activities:   
1 lying   
2 sitting   
3 standing   
4 walking   
5 running   
6 cycling   
7 Nordic walking   
9 watching TV   
10 computer work   
11 car driving   
12 ascending stairs   
13 descending stairs   
16 vacuum cleaning   
17 ironing   
18 folding laundry   
19 house cleaning   
20 playing soccer   
24 rope jumping   
0 other (transient activities)

**Relevant Papers:**

The following two publications describe the dataset and provide a baseline benchmark on various tasks of physical activity recognition and intensity estimation:   
  
[1] A. Reiss and D. Stricker. Introducing a New Benchmarked Dataset for Activity Monitoring. The 16th IEEE International Symposium on Wearable Computers (ISWC), 2012.   
[2] A. Reiss and D. Stricker. Creating and Benchmarking a New Dataset for Physical Activity Monitoring. The 5th Workshop on Affect and Behaviour Related Assistance (ABRA), 2012.   
  
Further information (detailed description of the protocol and the various activities, statistics of the dataset, the subjects, etc.) can be found in the documentation attached to the dataset. Please refer to the file readme.pdf.

**Citation Request:**

This dataset is freely available for academic research, there are no (legal or other) constraints on using the data for scientific purposes. We would appreciate referencing one of the below publications ([1] or [2]) if you use this dataset.   
If you have any questions or suggestions, please contact Attila Reiss ([firstname].[lastname]@dfki.de). Also, please let us know if you have any publications that uses this dataset.   
We recommend to refer to this dataset as the â€œPAMAP2 Datasetâ€ or the â€œPAMAP2 Physical Activity Monitoring Datasetâ€.   
  
[1] A. Reiss and D. Stricker. Introducing a New Benchmarked Dataset for Activity Monitoring. The 16th IEEE International Symposium on Wearable Computers (ISWC), 2012.   
[2] A. Reiss and D. Stricker. Creating and Benchmarking a New Dataset for Physical Activity Monitoring. The 5th Workshop on Affect and Behaviour Related Assistance (ABRA), 2012.

Set 6:

<https://archive.ics.uci.edu/ml/datasets/Activity+Recognition+system+based+on+Multisensor+data+fusion+(AReM)>

|  |  |
| --- | --- |
| **Abstract**: This dataset contains temporal data from a Wireless Sensor Network worn by an actor performing the activities: bending, cycling, lying down, sitting, standing, walking. |  |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Data Set Characteristics:** | Multivariate, Sequential, Time-Series | **Number of Instances:** | 42240 | **Area:** | Computer |
| **Attribute Characteristics:** | Real | **Number of Attributes:** | 6 | **Date Donated** | 2016-05-18 |
| **Associated Tasks:** | Classification | **Missing Values?** | N/A | **Number of Web Hits:** | 48693 |

**Source:**

Filippo Palumbo (a,b), Claudio Gallicchio (b), Rita Pucci (b) and Alessio Micheli (b)   
  
(a) Institute of Information Science and Technologies â€œAlessandro Faedoâ€, National Research Council, Pisa, Italy   
(b) Department of Computer Science, University of Pisa, Pisa, Italy

**Data Set Information:**

This dataset represents a real-life benchmark in the area of Activity Recognition applications, as described in [1].   
  
The classification tasks consist in predicting the activity performed by the user from time-series generated by a Wireless Sensor Network (WSN), according to the EvAAL competition technical annex ([[Web Link]](http://evaal.aaloa.org/)).   
  
In our activity recognition system we use information coming the implicit alteration of the wireless channel due to the movements of the user. The devices measure the RSS of the beacon packets they exchange among themselves in the WSN [2].   
  
We collect RSS data using IRIS nodes embedding a Chipcon AT86RF230 radio subsystem that implements the IEEE 802.15.4 standard and programmed with a TinyOS firmware. They are placed on the userâ€™s chest and ankles. For the purpose of communications, the beacon packets are exchanged by using a simple virtual token protocol that completes its execution in a time slot of 50 milliseconds. A modified version of the Spin ([[Web Link]](http://span.ece.utah.edu/spin)) token-passing protocol is used to schedule node transmission, in order to prevent packet collisions and maintain high data collection rate. When an anchor is transmitting, all other anchors receive the packet and perform the RSS measurements. The payload of the transmitting packet is the set of RSS values between the transmitting node and the other sensors sampled during the previous cycle.   
  
From the raw data we extract time-domain features to compress the time series and slightly remove noise and correlations.   
  
We choose an epoch time of 250 milliseconds according to the EVAAL technical annex. In such a time slot we elaborate 5 samples of RSS (sampled at 20 Hz) for each of the three couples of WSN nodes (i.e. Chest-Right Ankle, Chest-Left Ankle, Right Ankle-Left Ankle). The features include the mean value and standard deviation for each reciprocal RSS reading from worn WSN sensors.   
  
For each activity 15 temporal sequences of input RSS data are present. The dataset contains 480 sequences, for a total number of 42240 instances.   
  
We also consider two kind of bending activity, illustrated in the figure provided (bendingTupe.pdf). The positions of sensor nodes with the related identifiers are shown in figure sensorsPlacement.pdf.

**Attribute Information:**

For each sequence, data is provided in comma separated value (csv) format.   
  
- Input data:   
Input RSS streams are provided in files named datasetID.csv, where ID is the progressive numeric sequence ID for each repetition of the activity performed.   
In each file, each row corresponds to a time step measurement (in temporal order) and contains the following information:   
avg\_rss12, var\_rss12, avg\_rss13, var\_rss13, avg\_rss23, var\_rss23   
where avg and var are the mean and variance values over 250 ms of data, respectively.   
  
- Target data:   
Target data is provided as the containing folder name.   
  
For each activity, we have the following parameters:   
# Frequency (Hz): 20   
# Clock (millisecond): 250   
# Total duration (seconds): 120

**Relevant Papers:**

[1] F. Palumbo, C. Gallicchio, R. Pucci and A. Micheli, Human activity recognition using multisensor data fusion based on Reservoir Computing, Journal of Ambient Intelligence and Smart Environments, 2016, 8 (2), pp. 87-107.   
[2] F. Palumbo, P. Barsocchi, C. Gallicchio, S. Chessa and A. Micheli, Multisensor data fusion for activity recognition based on reservoir computing, in: Evaluating AAL Systems Through Competitive Benchmarking, Communications in Computer and Information Science, Vol. 386, Springer, Berlin, Heidelberg, 2013, pp. 24â€“35.

**Citation Request:**

F. Palumbo, C. Gallicchio, R. Pucci and A. Micheli, Human activity recognition using multisensor data fusion based on Reservoir Computing, Journal of Ambient Intelligence and Smart Environments, 2016, 8 (2), pp. 87-107.

Set 6:

<https://archive.ics.uci.edu/ml/datasets/UbiqLog+(smartphone+lifelogging)>

|  |  |
| --- | --- |
| **Abstract**: UbiqLog is the smartphone lifelogging tool that runs on the smartphone of 35 users for about 2 months. |  |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Data Set Characteristics:** | Multivariate | **Number of Instances:** | 9782222 | **Area:** | Computer |
| **Attribute Characteristics:** | N/A | **Number of Attributes:** | N/A | **Date Donated** | 2016-06-16 |
| **Associated Tasks:** | Causal-Discovery | **Missing Values?** | N/A | **Number of Web Hits:** | 24242 |

**Source:**

Reza Rawassizadeh rrawassizadeh **'@'** acm.org. University of California Riverside.

**Data Set Information:**

This is the first smartphone based lifelogging dataset that is going to be available for public use. Please consider that the user of this dataset are obliged NOT to perform any sort of analysis that can harm the privacy of participants. This dataset is not for any privacy related analysis that can re-identify users.   
The UbiqLog tool is open source and accessible here: [[Web Link]](https://github.com/Rezar/Ubiqlog)

**Attribute Information:**

With respect to users privacy UbiqLog collects their Calls, SMS headers (no content), App use, WiFi & Bluetooth devices in user's proximity, geographical location (if available and GPS works), physical activities form Google play API.   
Data format is in JSON, because there are different sensors and they have different variables. Nevertheless, we have the code for cleaning and converting the data into CSV + smoothing the time. Moreover, we can share our visualization code. Interested individuals could contact the given email address.

**Relevant Papers:**

To appear: Scalable Daily Human Behavioral Pattern Mining from Multivariate Temporal Data.

**Citation Request:**

Please cite both of the following paper and NOT only one of them:   
  
Rawassizadeh, R., Tomitsch, M., Wac, K., & Tjoa, A. M. (2013). UbiqLog: a generic mobile phone-based life-log framework. Personal and ubiquitous computing, 17(4), 621-637.   
  
Rawassizadeh, R., Momeni, E., Dobbins, C., Mirza-Babaei, P., & Rahnamoun, R. (2015). Lesson Learned from Collecting Quantified Self Information via Mobile and Wearable Devices. Journal of Sensor and Actuator Networks, 4(4), 315-335.

Set 7:

<https://archive.ics.uci.edu/ml/datasets/WESAD+%28Wearable+Stress+and+Affect+Detection%29>

|  |  |
| --- | --- |
| **Abstract**: WESAD (Wearable Stress and Affect Detection) contains data of 15 subjects during a stress-affect lab study, while wearing physiological and motion sensors. |  |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Data Set Characteristics:** | Multivariate, Time-Series | **Number of Instances:** | 63000000 | **Area:** | Computer |
| **Attribute Characteristics:** | Real | **Number of Attributes:** | 12 | **Date Donated** | 2018-09-14 |
| **Associated Tasks:** | Classification, Regression | **Missing Values?** | N/A | **Number of Web Hits:** | 16566 |

**Source:**

Philip Schmidt, Robert Bosch GmbH, Corporate Research, Germany, firstname.lastname **'@'** de.bosch.com   
Attila Reiss, Robert Bosch GmbH, Corporate Research, Germany, firstname.lastname **'@'** de.bosch.com

**Data Set Information:**

WESAD is a publicly available dataset for wearable stress and affect detection. This multimodal dataset features physiological and motion data, recorded from both a wrist- and a chest-worn device, of 15 subjects during a lab study. The following sensor modalities are included: blood volume pulse, electrocardiogram, electrodermal activity, electromyogram, respiration, body temperature, and three-axis acceleration. Moreover, the dataset bridges the gap between previous lab studies on stress and emotions, by containing three different affective states (neutral, stress, amusement). In addition, self-reports of the subjects, which were obtained using several established questionnaires, are contained in the dataset. Details can be found in the dataset's readme-file, as well as in [1].

**Attribute Information:**

Raw sensor data was recorded with two devices: a chest-worn device (RespiBAN) and a wrist-worn device (Empatica E4).   
The RespiBAN device provides the following sensor data: electrocardiogram (ECG), electrodermal activity (EDA), electromyogram (EMG), respiration, body temperature, and three-axis acceleration. All signals are sampled at 700 Hz.   
The Empatica E4 device provides the following sensor data: blood volume pulse (BVP, 64 Hz), electrodermal activity (EDA, 4 Hz), body temperature (4 Hz), and three-axis acceleration (32 Hz).   
  
The dataset's readme-file contains all further details with respect to the dataset structure, data format (RespiBAN device, Empatica E4 device, synchronised data), study protocol, and the self-report questionnaires.

**Relevant Papers:**

[1] Philip Schmidt, Attila Reiss, Robert Duerichen, Claus Marberger and Kristof Van Laerhoven. 2018. Introducing WESAD, a multimodal dataset for Wearable Stress and Affect Detection. In 2018 International Conference on Multimodal Interaction (ICMI â€™18), October 16â€“20, 2018, Boulder, CO, USA. ACM, New York, NY, USA, 9 pages. [[Web Link]](https://doi.org/10.1145/3242969.3242985)

**Citation Request:**

You may use this data for scientific, non-commercial purposes, provided that you give credit to the owners when publishing any work based on this data. Please acknowledge publication [1].   
We recommend to refer to this dataset as WESAD, or 'Wearable Stress and Affect Detection'.

**PRESENTATION SCRIPT:**

5 minute presentation

1. Introduction To The Challenge (1min)

As an employee of Lockheed Martin, my role is to provide technical strategy with respect to our simulation products, and support the development and enhancement of training solutions for our warfighters. At the beginning of the UCF Data Analytics and Visualization Bootcamp, we were asked to document what we expected from the program, and how we might apply it in our work place. To paraphrase what I recorded at the beginning of this 6 month intensive journey;

“I don’t expect to become an expert in these emerging technologies, but I do have some specific goals and problems to solve. I will be aiming to apply my learning to work-place tasks as I go through the boot camp curriculum. In particular, I would like to prototype and experiment with training data analytics as applied to the military training and simulation domain. The concept of an intelligent assessment and review of human and machine performance will require significant development of specific instrumentation and sensors to capture the right quality of data. I anticipate that some of this burden might be better handled with the adoption of machine learning, which would ideally discover business logic dynamically, rather than require much more laborious encoding and recording methods previously performed manually by the human / system performance analyst.”

For thousands of years, students and warfighters alike, have relied on observation and assessment conducted by their instructors and superiors at both training facilities and on the job training. {general footage of classroom instruction}

Providing timely feedback is vital to qualification and performance improvement of individuals and teams working together. The modern military training facility includes extensive utilization of closed-circuit television cameras, body cameras like the GoPro, and now Drone based cameras. {DRTS, UOTS, and Tomato Factory footage of CCTT and CCTT based AAR}

While the quantity of coverage is easily expanded over fixed and wireless range networks, this method does not ensure improved quality and consistency of measuring performance, and to some extent requires many more observers and instructors with different life experiences and knowledge applying their own personal spin on assessments. {TDK instructors)

This is neither efficient or consistent, in the way assessments are conducted and recorded. Silos of learning are unique to each training location, based on the individual instructor / observers, where knowledge is not easily accessible or tracked across the military enterprise. {Show mapbox view of military training locations across the globe}

As part of investments into Next Generation Training, Lockheed Martin works with small businesses and academia to research key areas in human performance, intelligent tutoring, and virtual instructors. {stock LM sims}

Working closely with the Nanyang Technological University in Singapore, an investigation was made into the use of Video Data Analytics to perform basic automated assessment of soldiers maneuvering through an urban operations training area. While the video analytic capability proved to demonstrate some potential, a common issue arose with respect to obscuration of the individuals. As soldiers bunch up together, refer to as stacking, their individual performance becomes obscured by the other trainees in close proximity. This issue is compounded by the tight quarters within narrow routes, stairwells and subterranean spaces. Ultimately, the visibility is almost completely obscured during night exercises and under the purposeful cover of smoke. Furthermore, the more instrumented the ranges become, the less representative they are of the battlefield. Commanders normally employ tactical sensors to monitor the execution of the mission in more austere environments like jungles, deserts, and megacities. {OWT, live fire training}

The alternative approach to traditional range instrumentation, is to instrument the warfighter. Enter the Digital Twin.

So how can we solve this challenge with the support of big data analytics and machine learning?

1. Research And Learning (1min)
   1. Former Research and Data Analysis Techniques

At the 16th IEEE International Symposium on Wearable Computers in 2012, A. Reiss and D. Stricker introduced the PAMAP2 Benchmarked Dataset created using three inertial measurement units, for Human Activity Monitoring. The PAMAP2 Dataset is currently hosted on the UCI machine learning repository. Data features include 9-axis IMU data streams for sensors on each of hand, chest, and ankle and subject heart rate. There are 1.9 million data points of 52 features each, spread over nine subjects. And 18 different activity IDs, including sitting, walking, running, folding laundry, and cycling.

In 2013, the IT4Innovations Centre of Excellence at the Technical University of Ostrava investigated classic and less commonly used classification techniques to recognize human activities recorded in the PAMAP2 dataset. Seven algorithms were compared in terms of their accuracy performance with the best classifier being based on the Orthogonal Matching Pursuit algorithm. Given the sensor technology that was used to create the PAMAP2 dataset, it was shown that activities performed in the database can be recognized reliably and with very high precision. In terms of recognition accuracy, the presented modification of the OMP classifier was shown to perform the best, however the precision comes at the price of significant time complexity. The fastest of the algorithms was NCC, but its recognition accuracy is not sufficient for practical use. From the speed/accuracy ratio perspective, k-NN seems to be the most reasonable choice as its accuracy performance is superseded by OMP2 only closely, but k-NN has a significant edge in computation times. For this reason, the main focus of future work in this area should be making the classifiers more efficient or finding a suitable preprocessing technique that would enable high-speed classifiers to provide better results.

Quite recent research conducted by Wainwright and Shenfield, published in the 2019 Athens Journal of Sciences, focusses on the use of the Long Short-Term Memory Technique to recognize human activity. The LSTM model for the experiments was developed making use of the Keras LSTM classifier with all of the code written in python. Wainwright and Shenfield conducted their research at the Sheffield Hallam University utilizing the NVIDIA GTX1050 GPU, presenting an alternative and novel approach to reliably detect human activities making use of smartphones. They highlight that detecting human activities making use of gyroscope readings poses many challenges due to the inconsistency of the data, thereby introducing interclass variability into the dataset. Referencing research conducted by Hassan in 2017, they state that the performance of any HAR research will be affected by the techniques used at each of the activity recognition process steps. Moreover, in any monitoring system the performance will be greatly affected by the sensor used. For example, the action of sitting to standing and then standing to sitting can be different in different environments and between different users. Human behavior changes and multiple tasks can be completed simultaneously therefore making it harder to correctly recognize an activity.

In this project, I compared the sklearn based Decision Tree, SVM, and KNN models for accuracy, execution time, and F-score for all accelerometer positions, as well as a Keras based multi-layer dense sigmoid encoded neural network running on an NVIDIA GTX1080 GPU. I also examined the mean heart rate and chest temperature of four subjects by activity, and ran a classification of activity intensity levels.

1. Discovery (1min)
   1. Automated Human Activity Recognition and Observation with ML
   2. Observability and Signature Management

Digital night vision capabilities provide the warfighter with an advantage on the battlefield. Thermal night vision goggles are expensive, and normally not issued for use on daylight training exercises or routine operations. That does not mean the modern enemy isn’t always equipped with them to observe our troops. One of the key observations made during this project was the significance of heart rate and core temperature features. While regular night vision cameras are not installed on all fixed ranges, the advantage of actively tracking warfighter heart rate and body temperature using body sensors, provides a special benefit in training and on the battlefield. Recent research indicates that the human body dissipates heat through the skin relatively proportionately across the entire body. This means that the core temperature measured on the chest, is a good indication of the temperature changes on the hands and head. By monitoring the warfighter’s core temperature in real time, and observing how it changes over low, medium, and high activity levels, we are now able to provide consideration for how the warfighter can maneuver, in order to minimize their thermal signature and observability.

1. Optimization (1min)
   1. Deep Learning, Efficient Maneuver, and Cognitive Support Tools

When a digital twin is established and maintained to a specific level of fidelity, individual characteristics can come in to play within the context of mission planning. While not everyone runs the same speed, can carry the same weight and maintain a running pace, or run the same continuous distances as others, Machine Learning can be utilized to provide the Small Unit Leader with recommendations to the mission execution plan, to ensure the whole team moves optimally. Have you ever heard of the saying “A buffalo herd can only move as fast as the slowest buffalo”? Based on data collected real time in the field, the Leader may be able to visualize the shortest route, estimate how long it will take his unit to arrive at the objective, and potentially redistribute weight and schedule in stops to ensure the team arrives alert and ready for battle. {TDK route planning}

For the individual, this may also include best route finding based on individual observability, optimum in route cover and protection, and calculated rest points to ensure heart rate and core temperature are managed at critical zones. {TULWAR video}

These kinds of cognitive support tools potentially replace the presence of a physical instructor, and improve decision making in real time. Information is envisaged to be displayed as an augmented overlay within a tactical helmet. {TULWAR video}

1. Next Steps (1min)
   1. Migration to Unity Linux target and NVIDIA TX2
   2. Migration to Intel Movidius Neuralcompute Stick and Raspberry Pi IoT

The tactical helmet displays are currently driven by embedded microcomputers utilizing low power wireless communications. These provide a means of connecting soldier sensors as well as other tactical communications and computing devices for enhanced situational awareness. The computers currently supporting augmented reality, utilize an NVIDIA TX2 GPU, which can be utilized to increase the performance of Machine Learning software components. Alternatively, the ML models can also be ported to a more common microcomputer such as the Raspberry Pi. Designed to easily integrate Internet of Things technology, the Raspberry Pi is a low-cost single board computer supporting Bluetooth, USB and wireless communications out of the box. It can also connect non-GPU based processors dedicated to Machine Learning, such as the Intel Movidius Neural Compute Stick. The combined cost of such devices is approximately $100, and run all of our favorite python modules, including Keras and TensorFlow.

The next step for this project will be to port the code and models to a prototype soldier system which includes all of the relevant and very latest biometric and position sensors, which will process the data into small packets of pre-classified information and distribute them to command processing nodes where they will feed Unit Leader Cognitive Support Tools and provide essential information to an Intelligent After Action Review Capability. There by increasing warfighter training readiness, supporting adaptive learning algorithms, and enhancing warfighter effectiveness and survivability in the battlefield.

[Android (RTAndroid)](https://git.embedded.rwth-aachen.de/rtandroid/downloads/raspberry-pi/)

[Ubuntu Mate](https://ubuntu-mate.org/raspberry-pi/) SD

[Windows 10 IoT Core](https://www.microsoft.com/en-us/software-download/windows10iotcore#!)