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Matthew Krugh
Clemson University

Ethan McGee
Clemson University

Stephen McGee
Clemson University

Laine Mears
Clemson University, mears@clemson.edu

Andrej Ivanco
Clemson University

See next page for additional authors

Authors
Matthew Krugh, Ethan McGee, Stephen McGee, Laine Mears, Andrej Ivanco, K. C. Podd, and Barbara Watkins

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Matthew Krugh[1], Ethan McGee[2], Stephen McGee[2], Laine Mears[1],
Andrej Ivanco[1], K.C. Podd[3] and Barbara Watkins[3]
[1]*Clemson University International Center for Automotive Research, Greenville, SC, USA.*
[2]*Clemson University School of Computing, Clemson, SC, USA.*
[3]*Robert Bosch LLC, Anderson, SC, USA.*
mkrugh@clemson.edu, mears@clemson.edu

Abstract
Assembly operations in the automotive industry represent a substantial proportion of overall manufacturing time and total manufacturing cost. With product complexity increasing year after year, humans continue to remain a cost-effective solution to the needs of flexible manufacturing. The human element is largely marginalized in Manufacturing 2.0 and necessitates a better understanding of the human's impact on the future of manufacturing. The work herein illustrates a method through the use of the Industrial Internet of Things (IIoT) to capture ubiquitous data streams from human and automated machinery with the intention to make available the data necessary and elucidate the potential to deepen the understanding of the human impact on Industry 4.0 assembly systems.

Keywords: Industry 4.0, IIoT, Quality

1 Introduction

1.1 Increasing complexity in automotive assembly

Automotive manufacturing is comprised of many diverse and critical processes that have continually become more complex with each iteration due to increased demand for quality and product variety and decreasing product life cycles. Automotive production is significantly characterized by assembly processes, which greatly contribute to the quality and cost of the final product. The BMW 7 Series for example has a projected 10^{17} number of variants in one product line [1]. With this increasing complexity and variety in vehicle assembly comes new opportunities for assembly defects to occur however it also lays many avenues for constant improvement and rapid innovation. On average, assembly activities account for 40% of product cost, up to 50% of total manufacturing cost, and 50% of total manufacturing time [2–4]. Having such a large impact on the cost and time to manufacture, it is readily seen how important defect elimination is to the success of the final product. This emphasis on defect elimination is compounded in automotive assembly where single defects may result in thousands of dollars of loss through rework or scrapping of entire vehicles.

1.2 Human workers in assembly

In the automotive market, there are many alternatives for a customer to consider during a purchasing decision so quality is a key factor in the decision-making process. The popularity of online reviews and easily accessible defect data, such as the annual Consumer Reports car reliability survey in the U.S.A. which has over 500,000 respondents, has pushed automotive manufacturers to adopt new practices and continually increase their internal quality initiatives to reduce assembly defects [5]. Manufacturers must maintain high quality standards while also maintaining a flexible and adaptive processes [6]. In manual assembly where human workers are assembling the products, [7–9] found that up to 40% of total defects resulted from operator error and that these defects are not always obvious.

In a 2015 survey on the automotive industry's view on the current state of quality and strategic path forward by Deloitte/Automotive Industry Action Group (AIAG) some of the major long-term concerns from original equipment manufacturer (OEM) and Tier suppliers as having the most significant impact on future quality were a lack of skilled workers and a lack of incentive for workers to select a career in the automotive industry [10].

Automotive manufacturing is becoming increasingly complex and technological and organizational structures have improved but little attention has been paid to the development of the production staff who will always be needed in flexible manufacturing [11–14]. The assembly line worker is an integral part of automotive assembly and [15] has shown that as automotive manufacturing systems have become more complex, worker technical knowledge and worker understanding of their machines has fallen.

As worker errors are not always obvious, they are difficult to control, and there is always a source for new issues such as quality inspection methods and guides that force a worker to alternate their attention between the assembly and the assembly instructions which can negatively impact assembly performance and result in expensive defects [8,16]. The lack of advancement in development of production staff is indicative of a need to develop a more effective feedback infrastructure between the human worker and future manufacturing systems as well as a deeper understanding of the underlying interaction between human and machine. Understanding this interaction will be vital to supporting a core aspect of Industry 4.0 to continually communicate between humans, machines, and products during production [17]. The Industrial Internet of Things (IIoT) incorporates leveraging big data, machine learning, sensor data, machine-to-machine communication, automation technologies, and human-to-machine communication to create a connected manufacturing ecosystem. This unified environment will enable inefficiencies to be pinpointed, root cause investigation, and support business intelligence. The research presented herein is a first step towards connecting the human operator into Industry 4.0 and the Industrial Internet of Things.

1.3 Pedestrian Dead-Reckoning

Pedestrian Dead-Reckoning (PDR) is a methodology utilizing sensors to detect steps, estimate stride length, and the direction of motion to estimate the movement of a person by starting at a known location and successively adding up position displacements [18,19]. PDR systems can also include ultrasound, radio, vision systems, and Global Positioning System (GPS) technologies, all of which are used to determine the movement of the subject throughout an environment. Indoor PDR presents a unique additional challenge in that accurate outdoor technologies such as GPS signals are not able to be reliably used indoors [20,21]. A common low cost sensor used in indoor applications such as for emergency responders and military personnel is a Micro-Electro-Mechanical (MEMS) Inertial Measurement Unit (IMU). IMUs contain an accelerometer, gyroscope, and magnetometer that is used to collect acceleration, rotational, and heading information from the subject. In the last decade, many methodologies have been proposed to estimate accurate indoor position and account for the inherent bias and drift in the measurement data but they typically detect and integrate step length and orientation to compute the relative position and orientation of a subject based around a designated absolute position with accuracies typically ranging from between 0.5-10% of the actual traveled distance [18–23].

1.4 Motivation/Objective

With the advent of Industry 4.0, ubiquitous data streams from manufacturing assets are being characterized and used for providing information to local and Enterprise level control systems. Though this holds great promise for improving productivity, quality and cost in production, the essential element of human influence has been largely ignored. In a manufacturing line with significant manual value-added content, this renewed focus on automated data streams, and the enabling of task automation can cause apathy or resentment in the human worker, as well as highlighting the fact that the human data and feedback mechanism is not being leveraged to the full potential. It is our intent with this work to explore the role of human data in production and quality characterization, and to quantify the marginal improvement possible through consideration of human signals in manufacturing. Considering human signals together with machine signals should generate additional, heretofore unexamined, information about process performance. This information can be utilized to better understand and control process output.

2 Problem Definition

2.1 Manufacturing Environment

The manufacturing facility studied is a Tier 1 supplier for the automotive powertrain industry producing parts directly for OEMs. They employ a Chaku-Chaku method of production, Japanese for load-load, which refers to a one-piece-flow where the only action an operator performs is load each machine in sequence [24]. Each station is fully automated and does not require human supervision during processing. Chaku-Chaku methods work to significantly eliminate work in progress (WIP), practice defect free production, and have very high space and labor utilization. An example of a real-world Chaku-Chaku production line can be seen in Figure 1 below. The grey arrow denotes the overall flow of material through the assembly line. A raw part starts at the beginning of both the blue and green arrows and they are then married or brought together to make up the final assembly after being processed.

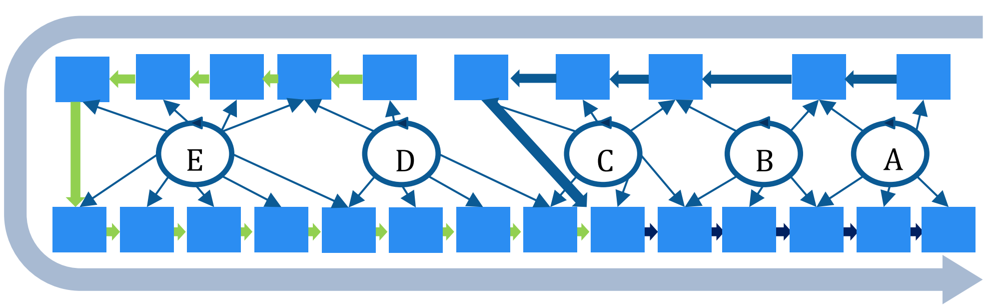

Figure 1. Chaku-Chaku assembly line, loops for individual workers denoted A-E

The assembly line typically consists of five workers moving through circles of machines denoted with the letters A-E above. The machines that a worker has been assigned to run is based on the process time and calculated to keep the line running smoothly and reduce idle time of both human and machine. With minimal idle time, even small disruptions can have significant effects throughout the process and with workers moving in circles, disruptions can propagate throughout the production line. Disruptions can consist of planned/unplanned maintenance, process failures, and machine failure. While disruptions to the production line can be simulated, a disruption's effect on the human workers and in turn back on the production line as each worker operates multiple machines is largely unknown and not measured in real world environments.

As each station is automated, the machine data consisting of start-stop times, light curtain triggers (signaling an employee was working within the machine), machine input and output, and machine up time were already being tracked by the facility. The machine data from each machine's history shows the station turnover time as shown in Figure 2.

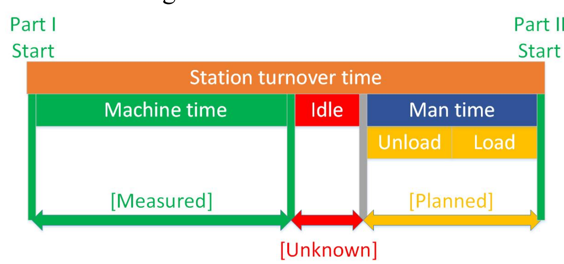

Figure 2. Breakdown of station turnover time

The station turnover time consists of three major areas, machine time, idle time, and man time. Machine time is the measured automated processing time of the machine to complete the task for a given part. Idle time is the time between when the machine has completed the automated process and when a worker unloads the finished part and loads an unfinished part. Man time is the estimated time a worker is unloading and loading parts before moving to the next machine. Apart from the measured start/stop times of the automated machine time, the unknown idle time and the planned but non-measured man time leads to a significant period of time that is unaccounted for. The movement data is expected to provide a reference for where the human worker is during the idle time whether two machines away or in front of the machine waiting for the process to complete to provide the production staff a better understanding of how well balanced the line is and are unexpected bottlenecks appearing.

While the planned idle time is at a minimum in a Chaku-Chaku assembly line, disruptions will affect the length of the idle time, potentially greatly increasing it and reducing the machine's time efficiency, as well as affecting the man time as the workers stride or consistency of movement is interrupted. The proposed human data to be collected is to be used to better understand this variation in the idle time. For example, is the variation in individual workers pace through their loops creating a negative effect over time, did a process change require that the line need to be rebalanced to account for unforeseen effects of the change, is there a difference in idle time variation between workers with different skill levels, or is there a collision in the paths that workers are taking as they move through their assembly loops. The answers to the plethora of questions about human-machine interaction have previously been answered predominantly by expensive or time-consuming trained observers.

2.2 Design requirements

Due to the limitations of the manufacturing environment, ethical/privacy concerns, industrial review board of Clemson University, and review by human resources department of the manufacturing facility, a list of design requirements was drafted to ensure that workers and production at the facility would not be negatively affected by the introduction of the measurement system and a summary can be found below.

A. The wearable portion shall provide movement data in addition to environmental data. Movement and location data shall be captured in the form of physical sensors such as accelerometers.
B. Sensors worn by workers shall communicate only within a short range of maximum 50 feet from the center of the assembly line. Readings of wireless sensors once the employee is 50 feet beyond the line should not be possible and if occur should be erased.
C. Future work may necessitate multiple lines being measured simultaneously within the same facility so a method of preventing cross-over lines is required.
D. The communication protocol shall not cause interference with machines present on the line and should be robust to moderate levels of interference produced by the automated machinery.
E. Sensors involving movement shall be read from at a rate of normally 10 hertz, not going below 5 hertz in the presence of extreme interference.
F. Sensors not involving movement shall be read from at one reading per minute to collect information about employee working conditions throughout the day.
G. The sensor platform shall not impede the work or safety of the worker or any surrounding workers.
H. The sensor platform developed or purchased shall encompass physical sensors and communication protocols that are battery powered.
I. Battery powered devices shall be capable of lasting through at least one 8-hour shift
J. A secondary location reading shall occur approximately every 1 to 5 seconds to verify the primary location data.
K. A fixed method of determining a workers place in their assigned loop shall be introduced to further verify the primary location data; however, this method may not interfere with the safety or productivity of the assembly line.
L. All data captured by the system shall be anonymous and not identifiable to any particular individual.

3 Development

3.1 System development and prototyping

To develop the software, select the hardware, and verify that the final system would meet the design requirements without having to purchase, program all of the parts, and conduct physical testing, the software/hardware modeling Architecture Analysis and Design Language (AADL) was used. AADL is designed for modeling IoT and cyber physical systems (CPS) systems to enable software developers to reduce their time to market and produce an accurate characterization of the final system, as up to 70% of errors are introduced in the design/requirements phases of the software development life cycle [25]. AADL provides tools for modeling, analyzing, and verifying a software and hardware design prior to implementation and enables hardware decision making early on.

Modern manufacturing environments are transitioning into high tech work areas where data from machines and computers is being generated and transmitted by the GB and TB per hour [26]. To keep the impact of the developed device low and to meet the above requirements, Bluetooth low energy was chosen as the communication medium between devices due to its short communication range in the presence of moderate interference (requirement A). The ability to assign and operate multiple devices to different receivers to avoid cross-talk (requirement B). As well as BLE's compatibility with the list of acceptable communication protocols that do not interfere with the machinery present in the manufacturing facility (requirement C). Wi-Fi was also evaluated but as it has a well-known characteristic of utilizing a much larger magnitude of power, it was deemed a secondary option to reduce the impact that device to device communication would have on battery life.

An example of how AADL was utilized in the design of the overall system was for the major design requirement battery life and wireless communication method which is typically a major power user in wearable devices as no processing was required on the sensor platform. Of the allowed wireless communication methods allowed by the facility, Bluetooth Low Energy had the historically lowest power utilization. It was proposed to test whether passive Bluetooth Low Energy communication may be sufficient for the data collection while greatly reducing the power consumption vs active communication which was assumed to have a higher power utilization. A visual comparison of active Bluetooth communication (**Error! Reference source not found.**) and passive Bluetooth communication (**Error! Reference source not found.**) are presented **Error! Reference source not found.**.

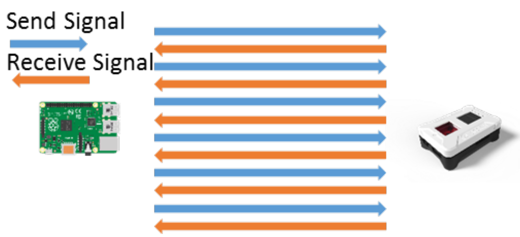

Figure 3. Active Bluetooth communication activity

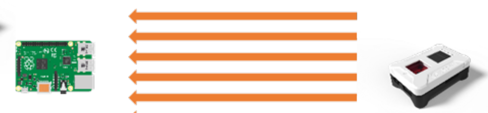

Figure 4. Passive Bluetooth communication activity

To keep power usage at a minimum, it was thought that the use of passive communication would provide the best method of allowing the device to operate for an entire 8-hour shift. However, as a typical manufacturing environment may have many machines from automated welders to robots starting and stopping continuously, the background interference level was considered to be an issue. It was unknown if the passive Bluetooth communication would be able to maintain a low latency connection in the presence of such interference which would negatively affect the transfer rate of data. Active BLE communication or IEEE 802.11n were also viable options as well but would require thorough and time consuming battery testing. Through the testing of a similar BLE 4.0 device within the labs at Clemson University International Center for Automotive Research which includes CNC mills and lathes, vehicle testing chambers, as well as myriad cell phones and laptops with high environmental Bluetooth and Wi-Fi background interference, the parameters for the software simulation could be estimated.

Through AADL simulation and testing, it was determined that passive communication, while providing a much longer battery life, would not provide proper data transfer rates due to achieving a maximum sample rate of 3 Hz. Active Bluetooth architecture provided an estimated sample rate of up to 10Hz. Requirements for the system were to sample at a rate of 10 Hz so the active Bluetooth communication was chosen. By using AADL during the initial phase of designing the proposed system, informed decisions such as these on hardware and system architecture were able to be made very early on. AADL also justified the investment in time for additional battery testing of the system.

After the transmission method had been chosen, the selection of the system's base stations began. While there were many alternatives on the market, the Raspberry Pi 3 was chosen to act as the receivers that were to be placed around the assembly line. This was due to its low cost (~$35USD) and that it contains a 1.2GHz quad-core ARMv8 CPU for simultaneous threading of collection, processing, and publishing of data, 802.11n wireless, Bluetooth/BLE 4.1, four USB 2.0 ports if peripherals were needed, and an Ethernet port. The Ethernet, Wi-Fi and BLE was expected to be needed to properly communicate with cloud storage and the sensing platform. Storage on the Raspberry Pi 3 receiver was kept to a minimum as all data was passed to and stored on a cloud server over Ethernet provided by the manufacturing facility. A series of five receivers were to be placed directly around the perimeter of the assembly line as seen in Figure **5**. Each receiver was running a standard copy of Jessie Lite Raspbian distribution operating system customized only so that BLE and server communication was enabled. By limiting the customization of the code and libraries used, the project could be readily applied in many different areas and facilities with limited additional development time. All code for the system was written using Python 2.7 with the redis, netifaces, bluepy and pymssql libraries installed.

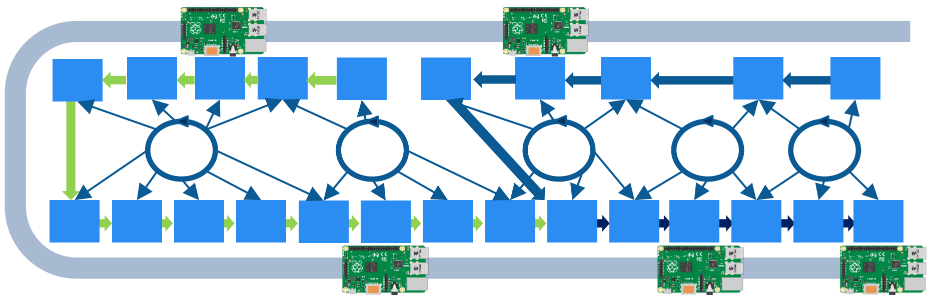

Figure 5. Placement of receivers along assembly line

The Bosch XDK prototyping platform was chosen for the mobile sensor as it was an off the shelf device which allowed acceleration of the system design process and included the sensors needed to meet the specifications required. The Bosch XDK consists of a BMA280 accelerometer, BMG160 gyroscope, BMM150 magnetometer, BMI160 IMU, BME280 humidity/pressure/temperature sensor, AKU340 acoustic noise sensor, and MAX44009 digital light sensor all capable of sampling at up to 1000Hz. Also included are built-in wireless 802.11 b/g/n, Bluetooth low energy (BLE) 4.0, 32-bit ARM cortex M3 microcontroller, and 560 mAh Li-Ion rechargeable battery (Requirement D). By selecting the pre-built mobile system, the mobile device was able to be rapidly prototyped and deployed.

For programming the sensor units, version 1.6.0 of the Bosch provided development environment was used. Each sensor unit was assigned a unique ID that identified it to the receivers around the assembly line to which the sensor unit was to be used. Each lines receivers would not know or connect to the IDs of sensor units from other assembly lines thus preventing cross-talk between the lines. Each receiver would establish a connection to one or more sensor units from their line and after the BLE pairing process completed, a signal would be sent to each sensor unit alerting it to start the sampling process. The accelerometer, gyroscope, magnetometer, and IMU were sampled at 10 hertz and were used to collect movement data. The environmental and light intensity sensors were sampled at 1 hertz and were sampled to collect environmental data throughout the shift as an additional source of signals that could potentially impact human performance. All samples were immediately sent to the receivers after being sampled. Due to the amount of uncompressed data generated by the system, approximately 1 megabyte every minute per sensor unit, the data was stored for approximately 1 minute before being transferred to a Microsoft SQL Server 2012 database server provided by the facility.

Trilateration of the devices was used as a secondary position verification method and to correct for inherent drift in the movement sensors. Trilateration determines absolute or relative coordinates by measurement the distances between a tracked point and three radial distances.

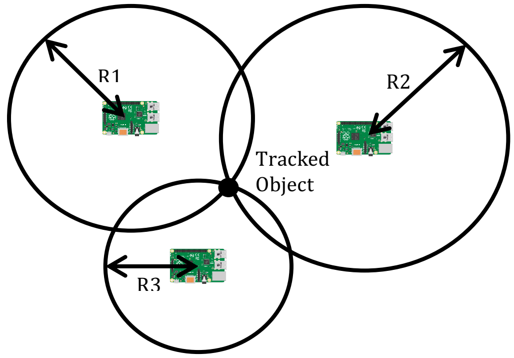

Figure 6. Bluetooth trilateration

In geometry, it is known that if a points lies on the perimeter of three circles with known centers and radii then there is sufficient information to determine the position of the point relative to the center positions. Through geometric derivation, the relative coordinates can be determined with:

$$x = \frac{R_1^2 + R_2^2 + R_3^2}{2d} \qquad y = \frac{R_1^2 - R_3^2 + i^2 + j^2}{2j} - \frac{i}{j}x$$

$$z = \pm\sqrt{R_1^2 + R_2^2 + R_3^2}$$

where, x and y are the relative coordinates of the tracked point assuming z=0 for the relative plane; d is the x-coordinate of point 2 relative to point 1; i & j are the x & y coordinates respectively of point 3 relative to point 1. The x and y coordinate output will provide relative coordinates in an arbitrary plane by assuming the centers of points 1, 2, and 3 all have centers at plane z=0 and point 1 is at the origin (0,0). When using more than 3 points of reference, the mobile devices are not always guaranteed to be using the origin point so a transformation is required to determine the tracked object position in the overall coordinate system.

$$\hat{e}_x = \frac{P2 - P1}{\|P2 - P1\|} \qquad \hat{e}_z = \hat{e}_x \times \hat{e}_y \qquad d = \|P2 - P1\|$$

$$\hat{e}_y = \frac{P3 - P1 - i\,\hat{e}_x}{\|P3 - P1 - i\,\hat{e}_x\|} \qquad i = \hat{e}_x \cdot (P3 - P1) \qquad j = \hat{e}_y \cdot (P3 - P1)$$

$$\vec{p}_{1,2} = P1 + x\,\hat{e}_x + y\,\hat{e}_y \pm z\,\hat{e}_z$$

where, $\hat{e}_x$, $\hat{e}_y$, $\hat{e}_z$ are the unit vectors in the x, y, and z direction respectively; P1, P2, P3 are vectors from the origin to the center of the circle; i & j are the signed magnitudes of the x & y component from P1 to P3; and $\vec{p}_{1,2}$ is the unit vector as expressed in the overall reference plane.

As a definite verification of position, a physical sensor was placed on the line. A pressure pad was placed at the start of each loop within the assembly line and connected to the receivers. The pressure pad had a 25lb activation pressure so that it was sensitive enough that only part of a foot would trigger it and was thermo-sealed to prevent oil and debris from interfering with operation.

3.2 Final system characteristics

A brief summary of how each design requirement was fulfilled is provided below.

A. Provide movement and environmental data: The XDK encompassed all necessary sensors.
B. Sensors communicate only within a short range: BLE employed will only communicate over approx. 32 meters, all data from past this range is erased by the receivers.
C. Prevention of cross-talk: Receivers only allow BLE pairing of designated sensor devices.
D. Cause no wireless interference with line equipment: Verified by plant personnel to not interfere.
E. Movement sampled at 10Hz: Optimized to allow 10Hz sample rates for movement sensors.
F. Environment sensors sampled every minute: Allows only one sample per minute collection rate.
G. Not impede safety or work: Verified by safety personnel to not impede the safety of worker.
H. Battery powered: The mobile system is battery powered
I. Battery should last one 8-hour shift: The battery used was tested to last more than 8 hours.
J. Verify location reading: BLE trilateration was utilized to verify the device location.
K. Fixed location reading: A fixed pressure pad provides an exact location for further verification.
L. Anonymous data: Devices are selected randomly before each shift by worker and data is not time stamped when provided to manufacturing facility.

4 Results

4.1 Machine data measurement

Two months of machine data was analyzed to determine the typical system parameters for the assembly line. Python 2.7.8 and R 3.1.3 were used for parsing the data and analysis. Takt time, unload/load time, part production vs planned production, material flow, and checks for formation of unintentional material buffers are examples of the extracted system parameters. The machine part output of two dependent stations, was as expected very similar in hourly production. Most gaps could be attributed to a variety of factors, including scheduled meetings, shift-changes, lunch breaks, or holidays.

It was found from the data that an easy to visualize method for determining timing on the production line was to check the synchronization of the marriage station where the two parts of the final assembly are merged together as seen in Figure 1. The synchronization was visualized by plotting the time that part A and part B arrived at the marriage station. A the slope of the line between the two time points as seen in Figure 7 below was used to determine how well synchronized the parts arrival was with a vertical slope indicating perfectly in sync production as both parts arrived at the same time, or a negative/positive slope indicating that one part reached the marriage station before the other and the order of arrival.

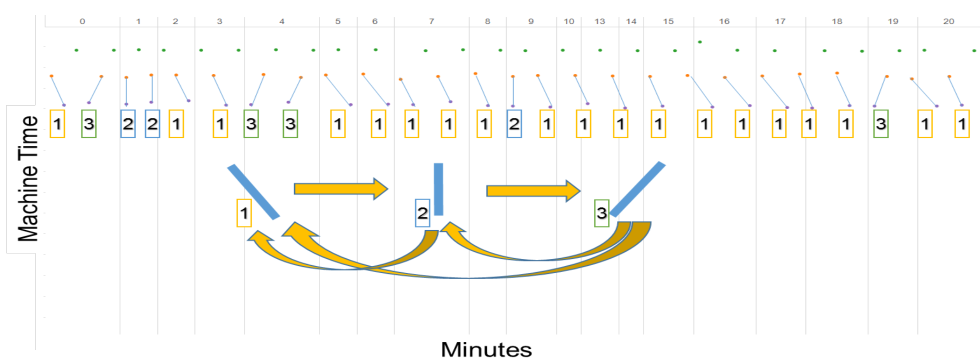

Figure 7. Marriage station synchronization per minute of production slopes (1) and (3) signify out of sync, slope (2) signifies in sync production

Synchronization of the marriage assembly was an indication of the material flow half-way through the assembly line. While the synchronization plot was a good metric for material flow, it did not help in explaining why parts had arrived at different times or when there was a greater than normal variation in the idle times. Through the machine data, the unload and load timestamps of a machine are known but variation in idle and man time are unaccounted for and a major target of the human-machine data.

4.2 Human Generated Signals

New sources of human signals in manufacturing enables additional insight into what is happening on the assembly line while the parts are in-transit between machines as well as while parts are awaiting inspection and transfer to other machines by human workers, how disruptions such as machine breakdowns and process failures affect the consistency of movement or stride of the human workers and the change in material flow as a gap is filled or created. The accelerometer, gyroscope, and magnetometer data collected during this work was converted into a position trajectory of the human wearing it. This was done using the widely used technique Zero Velocity Update (ZUPT) and is more thoroughly described in [19,21,27]. The basic process of ZUPT involves transforming captured data from the sensor frame into the global frame, estimating the integral of the data to obtain linear velocities, zeroing the linear velocity from drift at every step event (characterized by limited movement of foot sensor), obtaining the position increment at each step by integration estimation of the corrected velocities, and finally determining the Cartesian coordinate estimate of the sensor.

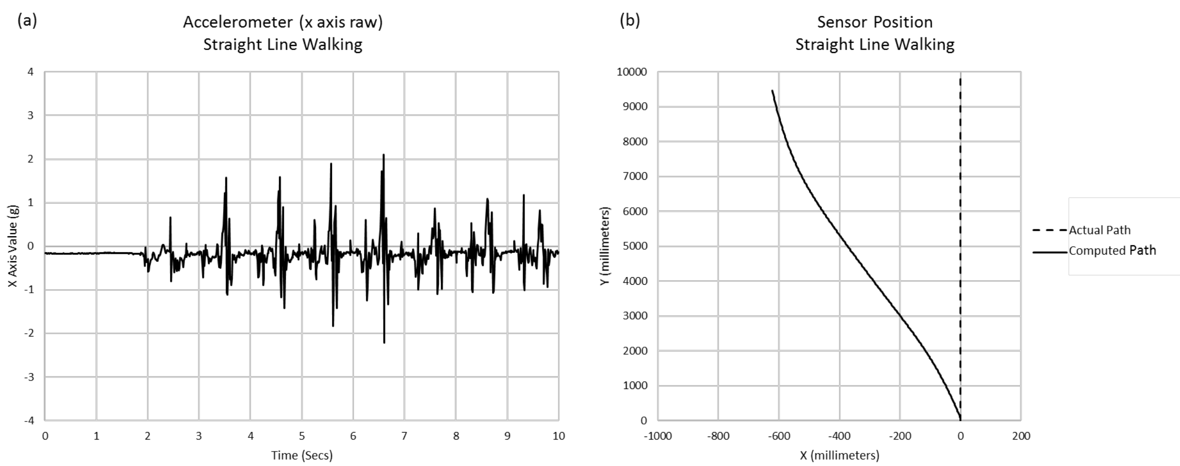

Figure 8. (a) Raw Accelerometer x axis first 10 seconds, (b) Computed position of sensor while walking a straight 10m path

5 Conclusions and Future Work

The raw accelerometer output and computed sensor position can be found above in Figure 8. Each footfall in (a) is evident but also seen is a large amount of noise and a bias is obvious in the first two seconds with no movement. One reason ZUPT is used in estimating the position of IMU's in PDR systems is its attenuation of sensor bias and drift inherent in MEMS sensors. As can be seen in Figure 8 (b), the computed position of the sensor as walked ten meters along a straight line demonstrated a best case error in final position of approximately -62 cm in the X direction and -48 cm in the Y direction. Error across all testing resulted in an average error of 7.4% of total movement distance. Based on previous work using ZUPT, the expected error was expected in the 1-2% range due to the limited distance and time that the measurement was completed [19,21,22]. A difference in error as seen here could result in an increase in expected error of approximately 300 meters along each axis without correction, assuming that a worker will walk 5 km in a typical 8 hour shift. Further work in correcting the output is necessary to his additional error. This will be done through implementation of a Kalman error estimation filter, the addition of a stride length estimation to the ZUPT algorithm as in [19] and using the pressure pads installed at the start of each loop to re-zero and remove built up error.

Future work for human-machine interaction includes exploring the prediction of disruptions and providing efficient mitigation strategies that allow for optimal production and to support business analytics efforts. Once the above improvements have been completed the human data will be integrated with the machine data, to establish patterns leading up to events such as machine down time or the unintentional buildup of parts. By using real/semi real-time machine data collected alongside the human data, patterns such as spending an increasing amount of time in front of a particular machine leading to subsequent unplanned maintenance events could be used to characterize that pattern as a potential indicative behavior leading to the non-value added event or used to preemptively predict these events before or as they occur and reduce the negative effects while aiding in reestablishing line performance. To directly assist the human worker, a deeper understanding of the human could be used to guide workers along an efficient path to recover from a disruption that may deviate them from their routine.

The human-machine interaction knowledge will provide benefits as the assembly line is adapted and machines and workers are added or removed. Production planning will be able to quantify the impact changes have on production and inform line staff in how their actions influence production performance. The human-machine interaction will also support future efforts to transition manufacturing facilities into Industry 4.0 where complete digital factories with simulated production help to account for discrepancies in the expected and actual production.

The systems utilized in this study are readily applied to other facilities due to the open requirements imposed. The pattern analysis methods to be used in future work are applicable but require modification to customize for changes based on product, process, and facility traits. The system developed in this work was predominantly off the shelf components and is quickly scalable depending on the needs of the facility. The facility in this research has already begun plans to expand the measurement system to additional areas to foster better understanding of the human workers and processes.

Presented in this research was a first step towards bringing the human worker online in Industry 4.0 manufacturing and investing in the understanding of assembly's most flexible system, the human worker. Data from a human on an assembly line can be streamed to and characterized by local and Enterprise control systems and could be used to make more informed decisions and quantify the effect on and from the human. Previously, one has been able to model the entire machine system in fine detail but the human element has remained largely unknown. Exploration of human data in manufacturing will leverage the full potential of the connected workplace of Industry 4.0. The human element proposed allows the flow of workers to be visualized and to better understand the human-machine interaction while also providing a reliance on human intelligence and ultimately reengaging the worker in the production system. This is facilitated by characterizing and merging data streams from manufacturing systems and wearable technology to quantify previously unexamined information about process performance and to better control process output.

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