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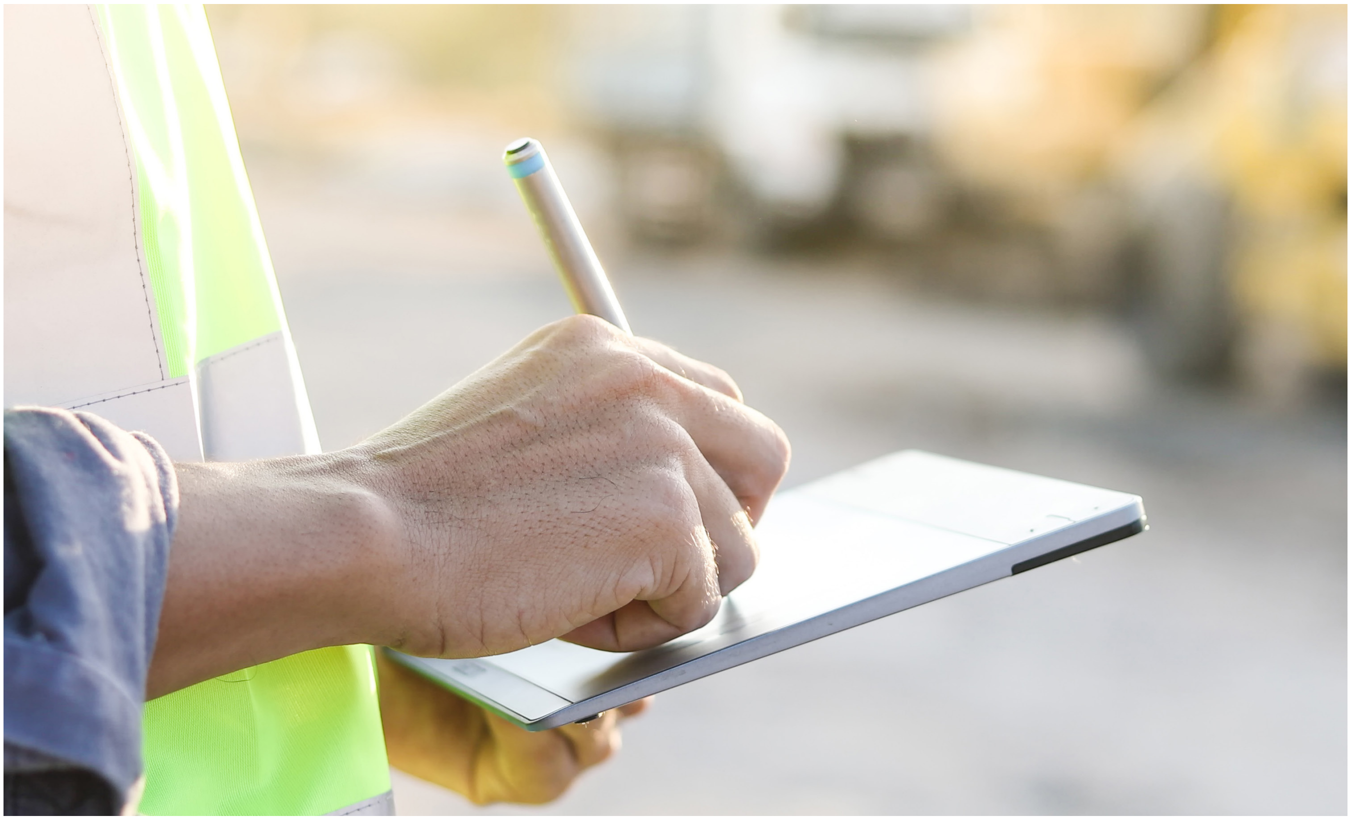
MOBILE SKILLS DEVELOPMENT

Implications of machine learning techniques, mobile guidance techniques, and intelligent personal agents for skills development of industrial field service workers



EXECUTIVE SUMMARY

Each day, military and civilian field-based maintenance and support personnel spend up to 70% of their day on non-productive activities - waiting, looking for information, or trying to understand what they should be doing next. Even when they are actively engaged in their work, they will do the job incorrectly 25% of the time. At the same time, there is a tremendous amount of data and analytics available from streaming sensors and enterprise data systems designed to help organizations make better decisions. Unfortunately, field-based workers rarely benefit from this information, resulting in little opportunity for improvement in workplace productivity.

This paper will discuss the potential of the (Industrial) Internet of Things as well as the application of mobile guidance in supporting field-based workers in the operation, repair, and maintenance of complex remote assets. The application of predictive analytics and delivery of curated guidance to field personnel on mobile and wearable devices, such as smart phones, smart watches, and head-worn wearables, proposes a dramatic shift in how work is accomplished on the last tactical mile. The determination of a user's true context is based on their digital ID (who they are and what their competencies might be), how they are feeling (based on physiological sensor data), and where they are (geographical location and what equipment may be nearby). These contextual data points can be processed by predictive curative algorithms to dynamically determine the minimal essential enterprise information that is relevant and critical to an end-user at any given point in time in order to guide them through a task, capture essential information, or better avoid workplace hazards.

CURRENT CHALLENGES

Each day, millions of men and women in thousands of organizations throughout the world spend up to 70% of their day on non-productive activities[1]. They are not idly wasting time, rather they are actively trying to find the right information, waiting for guidance, or attempting to coordinate with other work teams. While this condition exists throughout companies and across industries, it is particularly endemic within field maintenance and operations support teams in industries with remote assets. Exacerbating the situation is the human error rate. Once these workers have the information they need, they are still likely to do the job incorrectly 25% of the time[2]. Human error has the combined impact of unproductive repeat maintenance activity as well as the broader potential of catastrophic equipment failure and human injury. In addition to this direct impact, the indirect result of unproductive field maintenance personnel and human error is unplanned downtime, lost asset productivity, and failed outcomes.

The reasons for the current state of low productivity and high human error are as varied as the companies that experience the problem. The problem has been traditionally addressed with a patchwork of enhanced training solutions with a combination of classroom, on-line self-paced, and on-the-job learning coupled with knowledge refreshers to reduce skill fade. However, these approaches do not address the fundamental issue that stove-piped enterprise data systems remain disconnected and the field workforce has not been effectively enabled with the latest advances in mobility and analytics. Despite massive corporate investment in data capture and analytics, the application and benefits of that analytics remains constrained to the core of headquarters operations – enterprise efficiency and production optimization (opex), and capital equipment investment planning (capex). Workers in the field are rarely the beneficiaries except to be told that they are not working as effectively as corporate planners have determined should be possible.

Furthermore, because of ineffective data collection in the field, there is often an incomplete understanding of equipment maintenance issues. For example, from feedback we have received from prime equipment manufacturers in aerospace, defense, energy, and mining, maintenance issues are often attributed to being equipment failures or problems when they may equally be attributed to human error. Systemic human error in maintenance, caused by a variety of factors including language, culture, or unclear instruction, is rarely captured and identified. As a result, simple and inexpensive solutions such as updates to manuals and training or instruction materials are often overlooked in favor of equipment recalls and manufacturing re-work, with attendant costs that are magnitudes larger.

With the emergence of the Industrial Internet of Things (IIoT), there is an intense focus on making equipment smarter and self-optimizing using on-board sensors and remote or centralized analytics. The collected information is also being used to support maintenance

Each day, millions of men and women in thousands of organizations throughout the world spend up to 70% of their day on unproductive activities planning and pre-positioning of personnel and spares to accelerate maintenance processes. While the IIoT generates massive amounts of new data to support enterprise decision-making, it represents yet another silo of information that is rarely available to field-based personnel. The knowledge of the condition of the equipment around them would support the ability of field workers to make immediate decisions that could improve operations and efficiency and avoid equipment failures and lengthy periods of unplanned downtime[3]. The intelligence of equipment will continue to evolve and improve, but for the foreseeable future, field maintenance and operations crews will have a critical role in the continuous interaction of people and equipment.

Field maintenance and operations teams are the backbone of asset intensive industries. Field worker performance efficiency and situational awareness has a direct impact on enterprise productivity and economic performance as well as customer and employee satisfaction. As more data and information becomes available across the enterprise, the implications of that data needs to be in the hands of those in the field – where warms hands touch cold steel. Furthermore, insights and experiences from those working with the equipment in the field are a critical input to opex and capex planning. As a result, it is critical to enable these field maintenance and operations personnel with the most advanced technologies for bi-directional information delivery and capture, both to continuously improve their own performance and that of the overall organization.

SOLUTION

Since the advent of hand-held computing with smartphones and tablets, the efficacy of information delivery and capture solutions for field personnel has been a focus for development, experimentation, and analysis[4]. The potential value of making information available in a mobile form factor appears to be intuitive and research indicates that the use of mobile job aids can improve efficiency. However, current deployments tend to be restricted to one of two types: they provide mobile versions of existing data compilations, or they mimic paper-based information capture. The former includes tablet-based interactive electronic technical manuals (IETMs), virtual job aids on tablets, and mobile enterprise connectivity products. The latter include electronic work orders, mobile customer support systems, and safety and compliance reporting systems on phones and tablets. Recently, we have seen the emergence of new capabilities applicable to mobile guidance including remote video assistance, augmented reality, and wearable solutions such as smartwatches and smartglasses. These represent a significant opportunity for intelligent guidance when combined with decades of research in automated cueing techniques.

Existing strategies to deploy information on a mobile form factor take the view that, if information is accessible and portable, it will have inherent value and will be useful. The reality, unfortunately, is that field based workers have little time to spend trying to locate the information they require on a mobile device. It is not more information that they require; instead, they need smarter systems – systems that understand what information they need and get that information to them when they need it.

In efforts to increase location-based information relevance, video-based remote expert collaboration and guidance systems have been introduced. These systems enable an expert in one location to see a problem in another location and to assist a user in the remote location through verbal communication, on-line chat, or graphical overlay cues. Despite the technological accessibility, their deployment continues to be limited by technical issues such as network access and bandwidth and the practical requirement to have an expert available in real-time whenever the necessity for support arises.

With the emergence of augmented reality (AR), new techniques to deliver and collect information on mobile devices have also been developed and are being investigated[5]. These systems provide scripted cues and guidance to the user using text, graphics, and other media on a smartphone, tablet, or head-worn see-through display. AR systems use computer vision techniques to register and recognize their surroundings and navigation algorithms that extract information from on-board sensors to track the user's position relative to the object, ensuring that the cues are effectively correlated with the user's environment. While the potential for headworn AR systems provides the optimal blend of hands-free operation and limited context switching, in many industrial and field based-environments the state of the art in AR registration and tracking continues to face significant operational limitations[6]. In addition, the power and computing limitations of headworn wearables remain constraints for extended or disconnected operation. Technological advances will continue to decrease these limitations over time, and systems such as Microsoft HoloLens, used by NASA in remote maintenance guidance on board the International Space Station[7], are indicating where the potential may lie for AR and assisted guidance in field operations and maintenance.

Smartwatches and wrist-worn wearables represent another potential information delivery and collection user interface. With both on-board processing and remote tethered modes, smartwatches are able to deliver notifications, run local applications, and receive direct user input through voice and built-in keyboards. In addition, these devices contain a wide range of sensors that collect data on location (GPS, altitude), environment (UV, barometer), and physiology (heart rate, galvanic skin response) that can contribute significantly to the understanding of a user's condition and context. The utility of these devices to support field maintenance and guidance has not yet been explored, but the convenience and accessibility is worthy of study.

Decades of research has been conducted on the use of cueing techniques in high workload environments[8]. These techniques begin with an understanding of the user's local and physiological context and serve to either focus attention on critical items or remove the information noise within the operating environment. While much of that research has been focused on head-worn displays for military applications[9], cueing strategies are recognized to increase situational awareness, reduce user anxiety[10], and decrease cognitive workload. With the magnitude of the equipment-related information available from the IIoT and enterprise information systems, effective cueing strategies and workload classification algorithms have the potential to increase the effectiveness of field-based maintainers and operators[11] and should be explored further with mobile guidance solutions.

The combination of the emergence of AR and the power of tablets, smartphones, and wearables is driving a new era of context aware computing. The information available from sensors on most mobile devices enable an understanding of a user's location, their environment, and their physiology. Furthermore, with an associated enterprise digital ID, local context can be correlated with enterprise data. Context aware computing enables a new generation of mobile applications that are smarter, more relevant to the end user[12] and that are designed to determine and deliver the right information and guidance to the right user at the right time[13] , in a format appropriate to the user's active device(s).

IMPLICATIONS OF MACHINE LEARNING

Context aware computing is enabling a new category of mobile applications that provide user-centric in-situ guidance and recommendations. Evolving from general purpose agents such as Apple's Siri, Google Assistant, Microsoft's Cortana, and Amazon's Alexa, the next generation of intelligent personal agents (IPAs), or bots, are solution or domain specific and provide curated content related to specific user-centric use cases. In each case, today's IPAs fuse information from the sensors on the device to determine current context, identify contextually relevant information from the device (such as calendar and email content) and connected applications (such as social feeds and website history), and provide curated recommendations to the user for new actions[14]. Many of these new IPAs are consumer focused applications, providing everything from grocery reminders to restaurant recommendations.

IPAs in the enterprise environment are currently rare and are largely restricted to 'white collar' office applications such as finance approvals and salesforce automation. While some applications of IPAs have explored their use and benefits as advisory tools in operational environments such as unmanned vehicle control[15], little has been done to explore the potential for IPAs for industrial field maintenance and operations.

In parallel, the application of machine learning continues to evolve, becoming a virtually ubiquitous capability within the systems we use on a daily basis, from search engines to e-commerce and movie selection. Much of the application of machine learning in the industrial enterprise context has focused on optimization of analytics algorithms for equipment performance optimization[16]. Countless examples from research and practical experience have demonstrated its benefits provided that effective techniques for data preparation and learner selection are employed in the process[17]. Much as with IPAs, however, there is a dearth of activity applying machine learning to support the decision-making processes of a field-based worker.

LOOKING TO THE FUTURE

The proper application of an intelligent personal agent supported by machine learning will be able to delivery contextually relevant guidance to a field-based worker on a mobile or wearable device[18]. That capability will enable the worker to be more productive and make fewer errors compared to

traditional paper-based and current mobile electronic work guidance techniques.

A simple intelligent personal agent in the hands of a field worker will be able to understand that worker's local and personal context[19]. It will be able to reach across the range of IIoT and enterprise data to curate the appropriate and relevant information and deliver the necessary and sufficient guidance extracted from that information. In itself, this capability will reduce the unproductive time that a field worker spends looking for information, waiting for information, or coordinating with other workers. In addition, with the receipt of contextually relevant step-by-step guidance in real-time, the impact of skill fade should be eliminated and the number of mistakes a field worker makes in conducting a task should be drastically reduced.

With the application of machine learning and continuous equipment maintenance and individual performance feedback captured through the use of the IPA, the capability of intelligent assistance will be taken to a new level. Machine learning can be applied to continuously improve the algorithms that determine what guidance and knowledge is contextually relevant[20]. A worker's knowledge and performance changes over time; the enterprise performance objectives change over time; and, the extended database of equipment operation and maintenance grows and changes over time. Machine learning algorithms can be designed to consider these extended data elements and changing individual performance and expertise[21], and the learner can be applied to the curation algorithms to continuously adapt those algorithms to the personal, organizational, and equipment situational context[22]. The end goal: just-in-time, predictive guidance delivered by the IPA that is 'smart' – it continually changes and self-optimizes to ensure that the performance of the field worker is optimized. Much as machine learning is applied within predictive maintenance systems to ensure that machines self-optimize, similar techniques can be applied and delivered in an IPA to maximize the capabilities and skills of every field worker.

CONCLUSION

There is a need for technology-based solutions to improve the effectiveness and efficiency of field-based maintenance and operations personnel. Mobile hardware platforms, including smartphones, tablets, and wearable devices provide the potential to extract a more complete understanding of user context and, with appropriate information curation algorithms, deliver just-in-time individually-tailored guidance within an IPA. Furthermore, the continuous refinement of IPA information curation algorithms using machine learning techniques will enhance on-going relevance and optimization.

AUTHOR'S PROFILE

Carl Byers applies thirty years of experience in modeling and simulation, virtual environments, and augmented reality to software applications that improve knowledge-based productivity enhancement and decision making in complex distributed organizations.

As co-founder and Chief Strategy Officer at Contextere, Carl drives integrated R&D, product development, and collaborative partnerships. Carl serves as President of the AREA, a not-for-profit organization focused on accelerating the adoption of augmented reality in the enterprise. He is also co-founder and director of United World Voices, a registered charity dedicated to improving the lives of vulnerable persons and communities in Canada, India, and Africa.

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ABOUT US

Contextere is transforming the future of work using AI to deliver actionable intelligence to the last tactical mile, empowering your workforce and improving asset performance. Our products and services enable our customers to successfully navigate the fourth industrial revolution and global skills gap. Our machine learning algorithms extract previously inaccessible data, curate the information, and deliver knowledge that improves performance, increases skills, and eliminates errors.

Contextere works in the field with you to meet challenges head-on, supporting digital transformation, driving connected worker initiatives, and deploying our products to produce results for today and tomorrow.

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