Smart Phone Machinery Vibration Measurement

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Abstract—This paper presents a computationally economical algorithm that provides RMS value of vibration velocity calculated using the accelerometer measurements embedded in modern smartphones. This measurement extends the use of smartphones to quickly diagnose the health status of machinery. [1] [2]

TABLE OF CONTENTS

1. INTRODUCTION

Smart phones are pervasive in our life and its potential of growth is still very high. Due to their powerful processing capabilities, in addition to their primary role as the cellular phones, other applications were also eventually integrated into these devices – such as music and video players, internet browsers and other computer applications. However, lately more advanced and specific applications, often from unrelated domain areas, are being incorporated into these devices. Some of these advanced applications include GPS systems, video teleconferencing, travel service such as scheduling and purchases, music and voice recognition, image classification, music and video editing, garage door opener, boarding pass for air transportation among others. The smart phones are equipped with very compact and advanced processing platforms that besides other features also provide sophisticated sensing capabilities that are being exploited in many new applications. Among the sophisticated sensor suite of smart phones, the MEMS motion sensor that provides tri-axial acceleration information is of specific interest to us and is the focus of the current paper. In this work, a smart phone application, or an "App", for measuring machinery vibration with an acceptable level of precision is presented. Economical algorithms are developed to estimate dynamic acceleration and dynamic speed, which are commonly used variables that a vibration monitoring system uses and displays. The

results from the App are displayed in a bar graph format in multiple units that include acceleration in m/s^2 and in/s^2. For velocity a novel and simple algorithm is used to compute the peak and RMS values of the vibration signal. The displayed result includes the acceleration and velocity information along with their respective maximum values obtained during the measurement and subsequent processing. Information about normal operational conditions of machines according with the ISO 10816 norm based on the level of vibration, size of the machinery, and type of the foundation is also taken into account and relevant results are presented[1]. A color-coded result is provided on the display screen using green for good, yellow for satisfactory, orange for unsatisfactory and red for unacceptable levels of vibrations. The measurement and status report can be emailed to a designated user. In this particular work, the smart phone used is an iPhone® but the application can be easily transferred to other smart phone platforms as the hardware and processing requirements are nominal across most smart phones. The algorithm, vibration measurements, and vibration classification results based on the ISO norm are experimentally validated using periodic wave vibration test equipment providing an acceptable level of precision in the results.

2. SMART PHONE ACCELEROMETER

Most smart phones are now equipped with a standard three axes linear accelerometer. The primary function of this sensor is to determine the phone's orientation and interaction during such activities as games. Smartphone development platforms also allow the creation of applications that allow the processing and presentation of the acceleration data. The smartphone platform that is used in this paper is the Apple iPhone® 3GS® as shown in Figure 1.
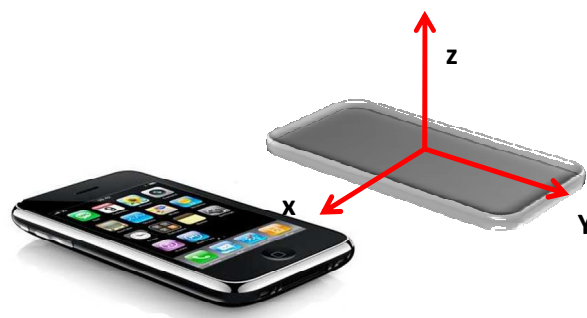

Figure 1: Apple iPhone 3GS and 3 accelerometer axes

The accelerometer sensor in the iPhone is a LIS302DL from STMicroelectronics that has a range of acceleration measurement of +/-2g to +/- 8g with a bandwidth of up to 400Hz [2]. The MEMS sensor requires 2.16 V to 3.6 V supply voltage and has less than 1 mW of power consumption. Also, it has the I2C and SPI digital output interface for data transfer and communication between peripherals.

3. VIBRATION MEASUREMENT NORM

The ISO 10816 norm suggests different levels of acceptable vibration depending on size and mounting of the machinery. The incremental level from an acceptable to an unaccepted stage is a proportional constant of value of 2.53 independent of the size and mounting (see Table 1) below. The level of the vibration velocity and the type of the machine determines the recommendation of good, satisfactory, unsatisfactory or unacceptable condition.

Table 1: ISO 10816 norm

Machine		Class I Small Machines (<15Kw)	Class II Medium *Machines* (15Kw< II< 75Kw)	Class III Large Rigid Foundation	Class IV Large Rigid Foundation
in/s	mm/s				
	0.01	0.28				
V	0.02	0.45				
E	0.03	0.71	GOOD		
L	0.04	1.12			
O	0.07	1.80			
C	0.11	2.80	SATISFACTORY		
I	0.18	4.50			
T					
Y	0.28	7.10	UNSATISFACTORY		
	0.44	11.2			
R	0.70	18.0			
M	0.71	28.0	UNACCEPTABLE		
S	1.10	45.0			

4. VELOCITY ALGORITHM

Traditionally the most common vibration measurement used by practitioners is velocity and not acceleration. The vibration velocity values measured from a system are compared with maximum values set by the manufacture or with the value suggested in the ISO 10816 norm. When the values exceeded the set values, the emergency alarm or safety switch should be triggered to stop the machine operations. In this paper, we present a simple heuristic algorithm to integrate the acceleration information in order to estimate the velocity. The main idea is to use the estimated velocity information as a comparison with that from vibration velocity measurement instruments.

Integration

Obtaining velocity from acceleration data in a real system is more challenging than it initially seems. The problem originates when integration of the acceleration to obtain velocity also integrates the error and bias that saturates the

output in just a few steps of integration. The sources of error can be attributed mainly to the measurement itself but numerical calculation could also introduce these errors. Industrial devices deal with this problem by resetting the integration computation periodically to avoid error accumulation. This is a good solution but is not suitable for continuous speed monitoring applications. Fortunately this error remains fairly constant and more importantly, can be dealt in the frequency domain. As long as the error comes from a frequency spectrum that is other than the measurement, a band pass filter can eliminated the error.

Based on the acceleration data, an algorithm was developed to calculate the velocity as shown in Equation 1.

$$v = \frac{x(n) + x(n+1)}{2} + \frac{W_a}{2} \sum_{i=1}^{n-1} \left[x(n-i) + x(n-i-1) \right] \ (1)$$

where $x(n+1)$ represents the current acceleration measurement and W_a can be [0.5:1].

W_a is the so-called *forget factor* and could be computed online by using autoregressive modeling [4-5] or have more complex function such as an exponential form. In this case, we chose a constant value called weighted forget factor. The training for determining the W_a value was conducted offline.

The velocity calculation algorithm was tested using actual real time acceleration data from a centrifuge and compared with the velocity data captured from an industrial monitor. Figure 2 shows data from a centrifuge and corresponding results using the algorithm shown in Equation 1. The three images are a portion (40 seconds) of a minute's worth of data taken approximately 2 minutes apart. The three sections of Figure 2 display the accelerometer data, velocity calculated from the proposed algorithm, and the velocity measured using a Bentley-Nevada monitor.
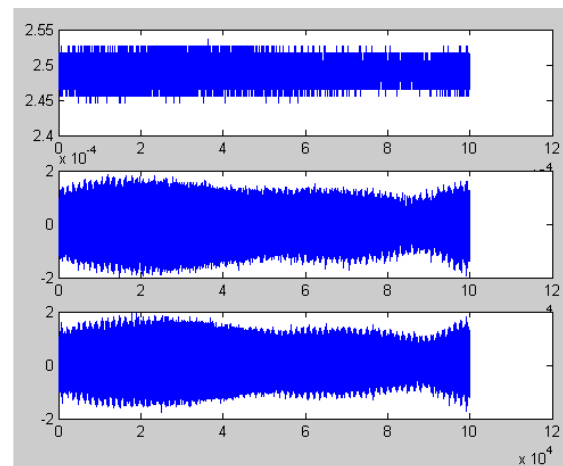

Figure 2: Centrifuge acceleration data and velocity comparison

The values and shapes of the two sections displaying the calculated and measured velocity, show validity of the algorithm developed in a real world operation. The speed was under 0.2 mm/s, which according to Table 1, is very good operation for a machinery class IV with rigid foundation

5. TEST BENCH

To test and validate the algorithm a test bench was instrumented and used to collect acceleration data. Figure 3 shows the test bench system that was implemented. The test bench comprises of a shaker (a modal exciter), a power amplifier for the shaker, a feedback accelerometer, a data acquisition (DAQ) system, and a PC to capture the acceleration data. The shaker is the TMS 2100E11 modal exciter with an output force of up to 100 lb and output frequency range of 0-5400 Hz.
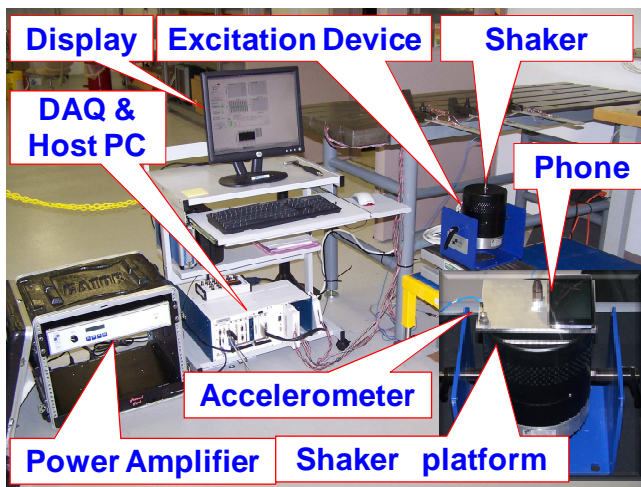

Figure 3: Test bench system

The shaker has a platform for placement of the smartphone and also incorporates a feedback accelerometer to ensure that the shaker output error was minimized. LabVIEW was used to implement a PID controller that ensures that the desired shaker acceleration setting error is minimized using the feedback accelerometer as shown in Figure 4.
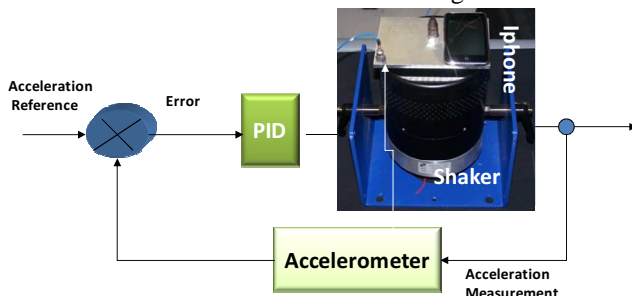

Figure 4: Shaker acceleration control loop

A LabVIEW GUI was developed to allow the settings of the shaker's test conditions to be quickly and easily set. The GUI is shown in Figure 5. The GUI also allows for visual

confirmation of the desired shaker output waveform and frequency based on the feedback accelerometer data. The GUI also allows for setting the desired acceleration levels and incorporates the PID control to ensure proper output voltage levels for the shaker to match the desired acceleration level.
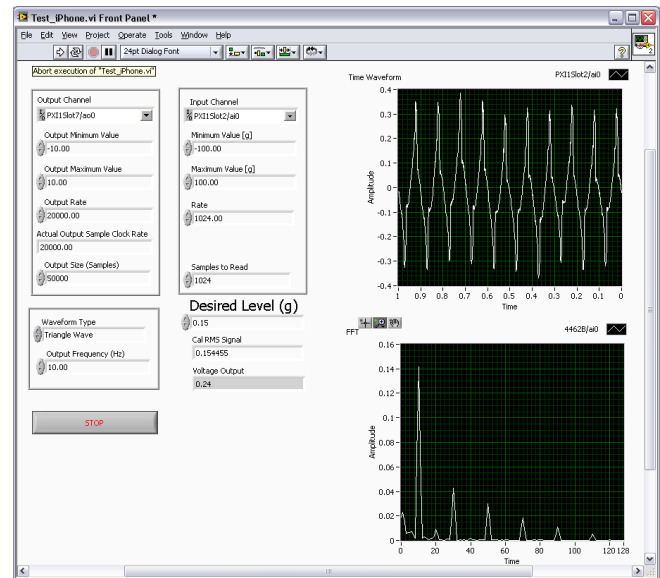

Figure 5: LabVIEW Graphical User Interface (GUI)

6. SMART PHONE APPLICATION DEVELOPMENT

An iPhone application was developed using GameSalad® authoring tool. This a graphical software, developed originally for videogame development, but can be used for rapid GUI development with internal data acquisition and mathematical and other processing capabilities. Using GameSalad an application was developed that continuously reads acceleration data from the embedded accelerometer. Figure 6 shows the smartphone with the application running that is continuously sampling the accelerometer data. The data is processed and displayed in various forms: acceleration, dynamic acceleration, velocity, and ISO norm.
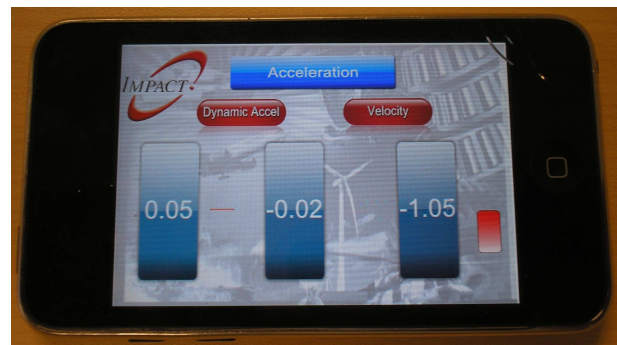

Figure 6: Smartphone with the App

Figure 7: iPhone application screen shots

The velocity algorithm from Equation 1 is implemented to calculate the vibration velocity. The app also calculates "dynamic acceleration" for the phone's vibration without taking out the influence of DC bias such as gravity. Figure 7 shows the screenshots from the application that displays the acceleration, dynamic acceleration, and velocity results depending on the selection made. The results are presented for each of the three axes and the bar levels for each axes and the numerical values are updated as the acceleration changes. The results can then be compared using the ISO norm table by pressing the "ISO Norm" button in the "Velocity" section as shown in Figure 7. The ISO norm also displays the highest velocity from either of the three axes that was captured during the previous "Velocity" section of the application. This helps in comparing the vibration-induced velocity with the industry standards for acceptable levels of velocity for a given class of machine.

7. EXPERIMENTAL RESULTS

To validate the accelerometer measurement of smartphone, raw accelerometer data was logged using an application that is able to log time-stamped acceleration data. The results from the smartphone acceleration and the output from the feedback accelerometer from the shaker were compared with satisfactory results. Figure 8 shows how close these measurements are for a reference 0.2g sinusoidal wave of 10 Hz.
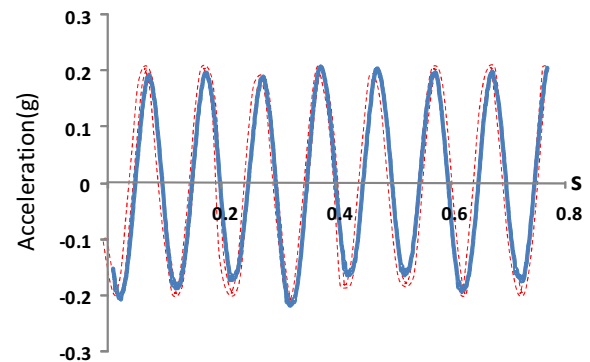

Figure 8: Accelerometer data from the smartphone (blue= solid) and feedback accelerometer (red-dash).

Figure 9 shows the process of integrating and calculating the velocity based on Equation 1 using the logged accelerometer data from the 10 Hz sine signal. The velocity in mm/s shows that v_{rms} is 26.43 mm/s, and according to the ISO 10816 norm that will be unacceptable ISO 10816 for any machinery with the exception for Class IV with a rigid foundation.
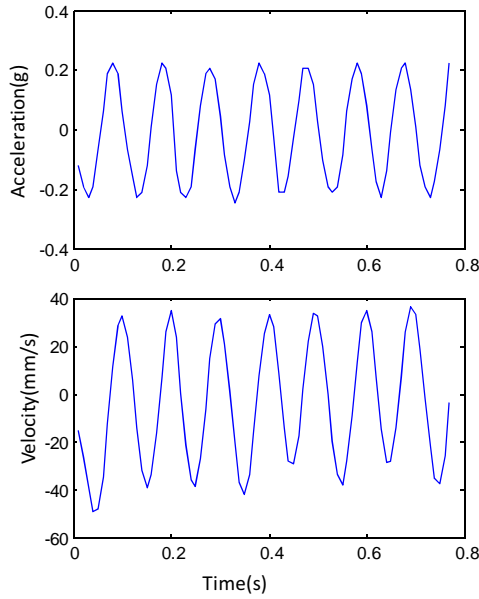
Figure 9: Acceleration and velocity computed from the algorithm for Wa=0.75 and 10 Hz excitation

In order to verify the proposed algorithm a set of sinusoidal waves were introduced to the system. Since the feedback accelerometer has a lower cutoff frequency of 3 Hz, equally spaced sinusoidal excitation waves were injected with the frequency range of 5 Hz to 20 Hz. The excitation waves were selected to be sinusoidal because they are simple in terms of analytical computations for integration. Figure 10 shows the results for the error between the theoretical and computed velocities. The results show a level of error with an average of 8%. This result is inside the margin of error for a quick measurement of vibration. This would be acceptable in most scenarios as we can observe from the ISO 10816 norm that changes in speed levels increment by 253%. Other factor to take into account is the evaluation of precision of the algorithm. Even though the reference was a pure sinusoid, the response of the excitation system included some dynamic perturbation that could have easily offset the theoretical computation of the velocity. However, the results that are shown in Figure 10 show the level of error across the range of frequencies that were tested to be an acceptable level.
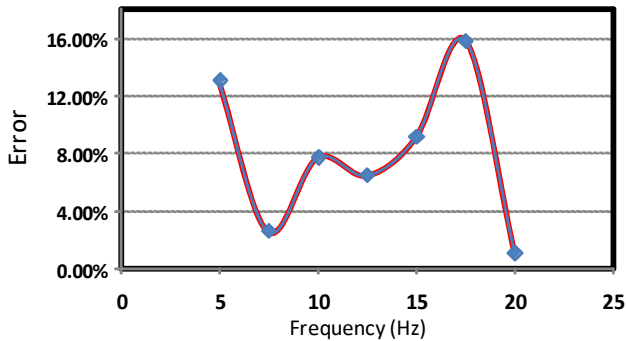

Figure 10: Percentage Error between the actual and theoretical wave integration

Finally, an example of a non-sinusoidal excitation is shown in Figure 11. The reference for the modal excitation system was set as a triangular wave at 5 Hz. Due to the cutoff frequency band of the feedback accelerometer, the output from the shaker poorly follows the triangular reference as is evident from the acceleration in Figure 11. Nevertheless, the overall shape is good and the results show the application of the velocity calculation algorithm in a non-sinusoidal application. The velocity of the vibration was computed to 23.28 mm/s.

8. CONCLUSIONS

This paper demonstrates the use of a smartphone platform to capture accelerometer data and use that information to calculate the velocity. As a matter of industry practice, the velocity information is used as an indicator of machinery health. The algorithm used to calculate the velocity integrates the past and present acceleration values. Future work should include methodologies to improve the velocity calculation. Specifically, online computation of the forget factor without the need to train the data set based on known results should be considered. Doing so, will allow precise calculation of the vibration speed ultimately leading to accurate machine health assessment.
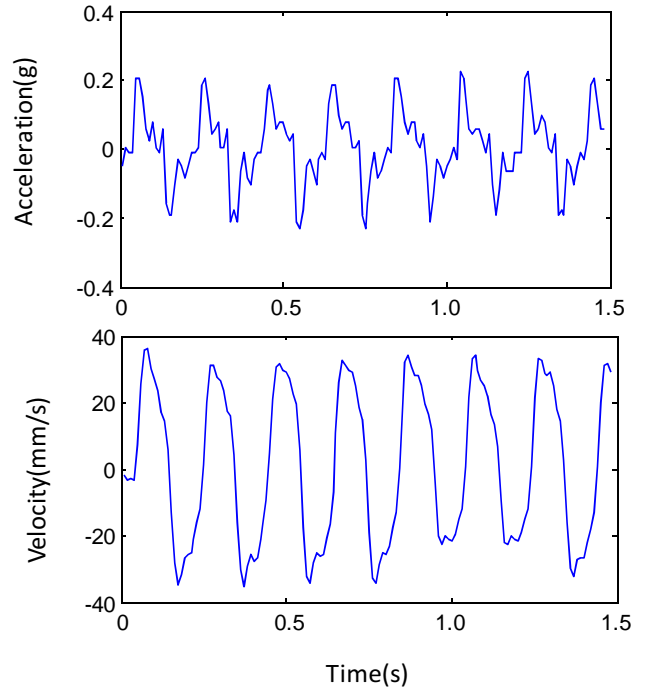

Figure 11: Velocity algorithm applied to non-sinusoidal shape

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BIOGRAPHY

Antonio E. Ginart (S'89–M'01–SM'07) *Received the B.Sc. and M Sc degrees in Electrical Engineering from Simon Bolivar University , Caracas, Venezuela in 1986 and 1990, respectively, and the Ph.D. in Electrical Engineering from the Georgia Institute of Technology in 2001. He has over 20 years of experience in motors, electronic drives, and industrial controls. He was an Instructor, Assistant Professor, and later Associate Professor at Simon Bolivar University from 1989 to 2002. He was a consultant for Aureal Semiconductors, Inc. in power amplification from 1999 to 2000, where he pioneered the effort to develop Class AD amplifiers. At Impact Technologies, he is responsible of developing intelligent automated monitoring systems for electrical and electronics equipment for industrial and military applications. He has served as principal investigator for several NASA and DOD SBIR projects. His research has led to over 50 publications and he is IEEE senior member*

Irfan Ali is a Project Engineer at Impact Technologies. He received a B.S. and M.S. in Electrical Engineering from Georgia Institute of Technology in 2007 and 2009 respectively. He has been a part of the Impact Technologies team developing innovative technologies for electronic system health assessment since joining. He has worked intimately over the past year with the research and development of the power device PHM technology. On the technical side he has developed algorithms, test plans and automated test benches in support of software and hardware product development. On the programmatic side he has led SBIR and commercial efforts in the health management areas of power supplies, industrial systems, and avionic data and systems.

Irtaza Barlas is currently Program Manager at Impact Technologies where he leads the research and eventual development of multiple products for the industry and DoD. He received his MS from the California State University in Sacramento in 1993 and a Ph.D. in Electrical and Computer Engineering from Georgia Institute of Technology in 2003. Before joining the Impact Team, he was a principal and Director of Software Development at Atlanta based Intelligent Automation Systems, where he led the development of several products related with image processing, and process monitoring in the wire and cable, and textile industries. Dr Barlas is a member of IEEE.

Antonio A. Ginart completed an internship at Impact Technologies during the summer of 2010, during which he worked developing applications for vibration monitoring for the iPhone platform. He also worked modeling the power output of hysteresis-based electric brakes. He is interested in programming languages with emphasis in Java. Currently, he attends Walton High School in Marietta, Georgia. He is planning to purse a degree in Computer Engineering.

Jeremy Sheldon is a Lead Engineer at Impact Technologies, specializing in bearing analysis, vibration diagnostics, signal processing, data analysis and collection. He also has significant experience with algorithm development, bearing modeling, and data acquisition system design. Jeremy holds a BS in Mechanical Engineering (Aerospace Option) from Rochester Institute of Technology. While at Impact, Jeremy has provided technical leadership on several programs relating to the bearing technologies. He has worked on numerous Phase I and Phase II SBIRs for the Navy and Air Force. These include an Air Force and Navy program focused on bearing diagnostics and prognostics. He is currently involved in a Phase III transition of SBIR developed bearing diagnostic technology for use by a major turbomachinery manufacturer. Also, he is leading the development of a bearing fault inference system, based on fuzzy logic, to automatically detect, isolate, and classify the severity of faults based on vibration analysis results. Jeremy has also provided technical support on several other vibration related Phase III contracts. He is a member of the American Helicopter Society (AHS) as well as the Secretary of the Machinery Diagnostics & Prognostics Committee within the ASME Tribology Division.

Patrick W. Kalgren has a B.S. degree in Computer Engineering from Penn State University and manages the Electronic Systems PHM group at Impact Technologies, leading the development of improved diagnostics and failure prediction to enable health management for electronic systems. Patrick has a 20+year background in mechanical and electronic system analysis, diagnosis and repair. While previously employed by PSU ARL, Patrick researched automated classifiers and developed performance tests to assess cross data type performance. At Impact, he has developed advanced signal processing, applied AI techniques to fault classification, researched advanced database design and supervised various software projects related to vehicle health management. Patrick is a member of Tau Beta Pi, IEEE, The IEEE Standards Association, and the IEEE Computer Society.

Michael J. Roemer received his Bachelor of Science degree in Electrical Engineering and his Doctorate in Mechanical Engineering from the State University of New York at Buffalo. He is the co-founder and Director of Engineering at Impact Technologies with over 18 years experience in the development of real-time, monitoring, diagnostic and prognostic systems for a wide range of military and commercial applications. He has extensive working knowledge in technologies such as artificial intelligence methods, vibration analysis, electrical signal analysis, aero-thermal performance monitoring, non-destructive structural evaluation and monitoring, and probabilistic risk assessment methods. Dr. Roemer is a past Chairman of the Machinery Failure Prevention Technology (MFPT) Society, Prognostic Lead for the SAE E-32 Engine Condition Monitoring Committee, Member of the IGTI Marine

committee and ASME Controls and Diagnostics Committee and Adjunct Professor of Mechanical Engineering at the Rochester Institute of Technology. He is the co-author of a recent book published by Wiley titled "Intelligent Fault Diagnosis and Prognosis for Engineering Systems" and has written or co-authored more than 100 technical papers related to integrated systems health management.