Feasibility of Intelligent Monitoring of Construction Workers for Carbon Monoxide Poisoning

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***Abstract*—This paper presents a feasibility study of a wearable computing system to protect construction workers from carbon monoxide poisoning. A pulse oximetry sensor has been integrated into a typical construction helmet to allow continuous and noninvasive monitoring of workers' blood gas saturation levels. To show the feasibility of monitoring for carbon monoxide poisoning without subjecting users to dangerous conditions, a prototype for monitoring blood O_2 saturation was constructed and tested during a user study involving typical construction tasks to determine its reliability while undergoing motion. As monitoring for O_2 and CO simply differ in the number of wavelengths of light employed, if monitoring O_2 is feasible, then monitoring for CO will be feasible as well. Using this equivalency, the results of this initial study show that integrating an oximeter into a construction helmet will warn the user of impending carbon monoxide poisoning with a probability greater than 99%.**

***Note to Practitioners*—This work addresses the issue of carbon monoxide exposure on construction sites. A noninvasive blood oxygen saturation sensor, called a pulse oximeter, was integrated into a typical construction helmet to investigate the reliability of continuous monitoring of construction workers. The pulse oximetry sensing technology was shown to be reliable under typical construction tasks such that a worker would be alerted of impending carbon monoxide poisoning before becoming impaired. Additional work is required with more complex tasks as well as isolating the sensor from motion artifacts generated by head movement.**

***Index Terms*—Biomedical monitoring, human factors, reliability.**

I. Introduction

THIS PAPER presents a feasibility study for a wearable computing system to protect construction workers from carbon monoxide poisoning. Carbon monoxide poisoning is a significant problem for construction workers both in residential and industrial settings. This danger exists because the exhaust from gasoline-powered hand tools can quickly build up in enclosed spaces and easily overcome not only the tool's user but co-workers as well. Of the construction-related inhalation deaths in the U.S. from 1990 to 1999, nearly 20% were due to carbon monoxide poisoning [1]. Reviewing carbon monoxide poisonings in Washington State, Lofgren [2] found the construction industry second to only wholesale workers in the number of reported incidents. Even more troubling, some workers knew the dangers of carbon monoxide poisoning and attempted to ventilate work areas, however, their efforts were not sufficient and they were still overcome [3]. Initial symptoms of carbon monoxide poisoning, such as headache, fatigue, and muscle ache, can easily be dismissed as symptoms of the work day and not as indicators of the onset of poisoning.

While the danger of carbon monoxide is known, current safety systems for construction workers only monitor environmental concentrations of carbon monoxide. This is insufficient because carbon monoxide exposure affects individuals at different rates based on their activity level, body size, and, more significantly, their background risk factors such as smoking, anemia, or prior exposure on the job site. Thus, environmental monitoring alone might not save the worker who is a daily smoker, or the person who has been sick and has a reduced red blood count as they may be overcome by carbon monoxide well before the environmental concentrations rise to the level of concern for their co-workers. In a large population, it is impossible to estimate all the potential physiological factors that will affect each individual worker. Therefore, it is desirable to monitor workers individually to avoid the shortcomings of environmental monitoring.

A successful individual warning system can then be tied into a construction site-wide warning system that can summon help for workers who are overcome before they can rescue themselves. The prototype described in this paper is the first step toward our vision of improving safety on construction sites by having a network of wearable personal protective gear, vehicles, tools, environmental sensors, and a site-wide planning and monitoring system. An intelligent construction site safety system would reduce injuries and fatalities by providing better protection from accidents, improving response times to accidents, and providing more thorough data collection that can be used to analyze accidents and near-accidents to prevent future occurrences.

To assess the feasibility of individual monitoring of construction workers, we integrated a pulse oximetry sensor into a typical construction helmet to noninvasively monitor the hemoglobin concentrations of the wearer. As explained in Section II-B, we conducted this study with a blood oxygen sensor to avoid exposing subjects to harmful environments, but without loss of generality towards carbon monoxide exposure. A user study was conducted to validate the prototype under typical construction tasks and assess the effect of motion on the sensor's performance. As this is the first study to monitor workers in real time, novice users were selected for the study. Novice users are more readily available and allow the

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device to be rapidly tested to determine basic feasibility of the design. Additional tests with typical construction workers are warranted, but only if the helmet can pass these initial studies. The results of the study show that the helmet can reliably monitor blood O_2 concentrations such that if exposed to carbon monoxide, the wearer will be warned before becoming impaired with a probability greater than 99%.

This work presents a novel analysis of the reliability of helmet-based pulse oximetry while undergoing motion. While previous works have explored the use of pulse oximetry during motion [4], [5], no study has classified the behavior of motion artifacts to determine the reliability of obtaining a valid measurement during a given time period. By characterizing the behavior of the pulse oximeter as a repairable system, we can build a theoretical model to estimate sensor reliability. A user study was conducted to verify the theoretical model as well as provide construction-like activities to measure the reliability of the helmet. In addition to creating a model for sensor reliability, this study also presents physiological and wearability analysis that directions the placement of the sensor within the helmet.

The remainder of the paper is organized as follows: Section II describes the prevalence of workplace carbon monoxide poisoning, a review of pulse oximetry, and related work in wearable pulse oximetry. Section III outlines the wearability requirements required when designing for construction workers and motivates placement of the sensor. Section IV describes the design and construction of the helmet prototype including estimates of battery lifetimes. Section V discusses the repairable system methodology, estimation of physiological profiles for construction workers, and user study performed to validate the design. Section VI discusses the results of the user study. Section VII presents conclusions and future work.

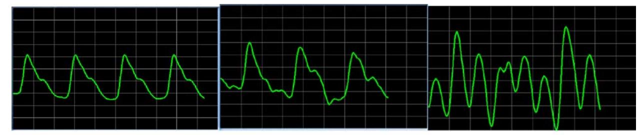
II. Background and Related Work

A. *Prevalence of Carbon Monoxide and Workplace Incidents*

Carbon monoxide is a colorless and odorless gas that is highly toxic to human life. When inhaled, carbon monoxide competes directly with oxygen in binding with hemoglobin. Carbon monoxide has an affinity for hemoglobin over 200 times greater than oxygen [6, p. 43]. This binding creates a new dysfunctional hemoglobin called carboxyhemoglobin (COHb) and greatly reduces the number of potential oxygen carrying hemoglobins (HbO_2). If the concentration of carboxyhemoglobin becomes too great, normal oxygen transport is interrupted, leading to cellular hypoxia and eventually death.

While the effects of carbon monoxide vary with internal concentrations, at 30% blood saturation the low level effects include headache, fatigue, and fainting. At higher levels, approaching 60%, a person will become unconscious and if not rescued, continued exposure will result in death [7]. As carbon monoxide diffuses in both directions across the lung-blood barrier, if presented with oxygen, a person will eventually exhale the carbon monoxide present in their body and recover [7, p. 1466].

Carbon monoxide exposure is a grave concern in the construction environment because of the many gasoline powered tools, generators, and vehicles that are common on the construction site. A report by NIOSH [3] highlights the danger of carbon monoxide exposure to construction workers. The majority of cases described involve workers using individual power hand tools such as pressure washers or concrete saws. In a majority of cases, workers were overcome in less than 30 min. Additionally, some workers knew of the danger and attempted to ventilate the areas, but their efforts were not sufficient.



(a) (b) (c)

Fig. 1. Pulse oximeter output showing volumetric changes in blood over several heart beats. (a) Typical signal with no errors present. (b) Signal with errors when sensor location moves from side to side and (c) up and down.

B. *Review of Pulse Oximetry*

To monitor workers for the presence of carbon monoxide, pulse oximetry is used to noninvasively measure hemoglobin concentrations in the blood stream. Pulse oximetry is an application of Beer's Law, which relates the attenuation of light through a medium dependent upon the compounds it passes through [6]. In the case of pulse oximetry, as light passes through vascular tissue, it is absorbed at different rates and frequencies for each species of hemoglobin. For each absorber of interest, a different wavelength of light is required.

An oximeter consists of a set of light-emitting diodes (LEDs) of different wavelengths and a photodetector (PD) to receive the emitted light. The relative geometry between the LED and the PD allows for two different oximeter configurations: transmissive and reflective. For a transmissive design, light shines through the tissue and is received on the other side by the PD. In a reflective design, light reflects off a surface within the body, such as bone, and returns to the PD. In this study, a reflective oximeter configuration was selected based upon the wearability analysis in Section III.

In using pulse oximetry, a photopleysmograph (PPG) is created, showing the volumetric changes of blood through the monitoring site. The PPG value rises and falls as the heart pumps blood through the body with each peak in the signal indicating a heart beat. A typical PPG signal is shown in Fig. 1(a). A person's hemoglobin concentration is found by comparing the relative values of the maximum and minimum points of the PPG signal for each frequency of light. However, errors in calculating the concentration can occur when the person moves, because the blood volume at the measurement site will change due to the motion rather than the heart beat, as shown in Fig. 1(b) and 1(c). These motion induced errors we term as *motion artifacts*.

1) Equivalence of $SpCO$ *and* SpO_2 *Oximeters:* Since pulse oximetry has traditionally focused on determining blood oxygen saturation only two wavelengths of light have been used, as shown in (1). The LED wavelengths are commonly selected in the red (R) and infrared regions (IR) because Hb and HbO_2 exhibit different absorption characteristics in these regions, making it possible to distinguish their individual absorptions [6, p. 46]. Since SpO_2 is only based on Hb and HbO_2 concentrations, the attenuations in the red and infrared can be used to find a "ratio of ratios" shown in (2) that is directly related to the oxygen saturation [6, p. 130]

$$\mathrm{SpO_2} = \frac{[\mathrm{HbO_2}]}{[\mathrm{HbO_2}] + [\mathrm{Hb}]} \tag{1}$$

$$\mathrm{SpO_2} \approx R = \frac{\ln\left(\frac{I_{\min,R}}{I_{\max,R}}\right)}{\ln\left(\frac{I_{\min,IR}}{I_{\min,IR}}\right)}. \tag{2}$$

The ratio R, is not itself the internal $\mathrm{SpO_2}$ levels, but can be empirically related to $\mathrm{SpO_2}$. Typically, this is done via calibration by inducing hypoxia in subjects and noting arterial $\mathrm{SpO_2}$ and R values [8]. The calibration is costly and usually performed by oximeter manufacturers for each new design and the calibration values are used for oximeters in that series.

For each hemoglobin concentration of interest, a unique wavelength LED is required. Typically, in determination of blood oxygen saturation ($\mathrm{SpO_2}$), two LEDs are required. For blood carbon monoxide saturation (SpCO), up to seven LEDs are required to distinguish between carboxyhemoglobin and lesser dysfunctional hemoglobins [9]. However, the difference between the two sensing technologies is simply the number of light wavelengths employed.

A key assumption in this feasibility study is that we can determine how the pulse oximeter would respond in the presence of carbon monoxide without having to subject participants to dangerous environments. As described in the previous paragraphs, SpCO and $\mathrm{SpO_2}$ sensors are both based on the principles of Beer's Law and are of similar construction; they simply differ in the wavelengths of light used, i.e., in the number of LEDs employed. Both SpCO and $\mathrm{SpO_2}$ sensors are susceptible to the same motion artifacts. Thus, we can use a $\mathrm{SpO_2}$ sensor to understand how the technology performs during construction tasks, without having to expose subjects to carbon monoxide. Consequently, if we can show that $\mathrm{SpO_2}$ oximeters are reliable in construction environments, then by their equivalent construction, we can be confident that SpCO oximeters will be reliable as well.

C. Wearable Pulse Oximetry

While many oximeter designs are "wearable," few have been tested in real-life environments that would be required by a product to be deployed on a construction site. Additionally, many oximeter designs have been tested while undergoing motion, usually this motion is simply walking on a treadmill, shaking a hand, or a random tapping of the fingers. More complex tasks have been performed by Johnston *et al.* [10] and Nagre *et al.* [5] that involved a helmet-based oximeter undergoing simulated military activities that examined forehead, jaw, and chin locations that were integrated into a military helmet. Their results were compared to a finger-based oximeter to determine, relative to each other, which location was best. Additional work in helmet-based oximetry was conducted by Dresher who investigated the optimal pressure required to maintain a good measurement signal from the forehead and developed a fitted military helmet insert to allow proper blood flow [4], [11].

TABLE I
COMPARATIVE STUDIES OF OXIMETER PLACEMENT

Author	**Locations Compared**	**Motion**	**Preferred Site**
Mendelson *et al* [13]	forehead[R], finger[T]	N	forehead
Mendelson & Pujary [14]	forehead[R], wrist[R]	N	forehead
Narge & Mendelson [5]	forehead[R], finger tip[T], jaw[R], chin[R]	Y	forehead
Nogawa *et al* [15]	forehead[R], chest[R]	N	forehead
Rhee *et al* [16]	fingertip[T], finger[R]	Y	finger

While these studies are useful as a starting point for a construction helmet, the work presented here is distinct in several ways. First, because of differences in the helmet (e.g., a military helmet has a chin strap to hold it in place whereas construction helmets do not) and the activities tested, previous conclusions about motion artifacts may not apply. Additionally, our study deals with the motion artifacts directly, while some studies have manually removed those effects from the data set [11]. Second, Dresher monitored his subjects during breaks while the subjects were motionless by comparing the forehead sensor results to a finger-based oximeter to determine accuracy of the helmet [4, p. 26]. Third, while both systems monitor from the forehead because of physiological and motion-resistance concerns [4, p. 9], our treatment is more extensive concerning the wearability for the construction worker by comparing other potential locations such as the finger, ear, and hand.

III. WEARABILITY FOR CONSTRUCTION WORKERS

Physical design in wearable computing is different than in other computing fields. Not only must the form and functionality of the computing elements be considered, but also the impact of those elements on the human body. As described by Gemperle, the wearable computer must follow guidelines that meet the human form in terms of placement, form language, and movement [12]. Applying those guidelines to the construction population, we must seek a design that is comfortable to wear and does not interfere with their daily tasks, and also attaches at a location that permits monitoring of the worker. Furthermore, we require a design that can be worn year round, which rules out seasonal clothing such as overalls or coats, and we would like a design that workers will find socially acceptable. In the end, a balance must be struck between comfort, usability and feasibility.

In terms of placement on the body, we first consider the locations where pulse oximetry has been shown to be feasible. Having these locations, we can then assess each one in terms of wearability considerations to find an appropriate solution for construction workers. There are several body locations that have shown to be acceptable monitoring locations for pulse oximetry including the finger, wrist, earlobe, forehead, and facial regions. Table I summarizes several comparative studies of oximeter sensor placement. The table shows the types of sensors compared, where [R] denotes a reflective sensor and

[T] denotes a transmissive, whether the subjects were in motion or at rest, and which measurement site provided the best result.

The finger has long been the traditional measurement location of pulse oximetry with one of the first wearable designs being a large ring where the oximeter was housed [16]. Furthermore, measuring from the fingertip is very common in hospital settings and many medical devices use this location. Finger designs are usually envisioned as sensors embedded into a ring shaped housing, whereas designs on the fingertip typically clip on to the end of the finger. Wrist-based monitoring has also been attempted [14], [17], but the wrist's complex bone structure does not lend itself to being a stable location for light backscattering.

In terms of wearability, finger-based designs restrict the dexterity of the worker because each design covers a significant portion of the finger. Considering the target population often works with hand tools, it is unlikely that any designs encumbering the hands will be accepted. Furthermore, in a field deployment, measurement from the finger suffers in cold weather because of decreased perfusion in the extremities and is subject to frequent motion artifacts from movement and impact to the hands.

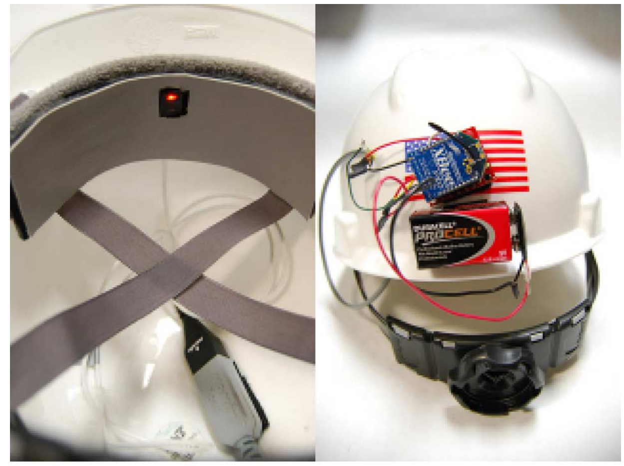
Early oximeter designs also used the ear as a potential location, but no comparative study has been performed to compare measurement on the ear to other locations. Early designs encased the entire ear and were uncomfortable. More recent designs have integrated the sensor within a common Bluetooth ear piece [18], potentially making the device desirable to be worn.

Several studies have examined regions of the face for possible oximetry monitoring including the forehead, jaw, and chin [5], [10]. These studies integrated the oximeters into the headband and chin straps of a military helmet. They found that during motion or even talking the jaw and chin sensors would be unusable due to motion artifacts. During combat simulation exercises, the forehead sensor was found to be less affected by motion than chin or jaw sensors.

From the analysis above, the most likely measurement locations are the hands, the ear, and the forehead. Among these three locations, we choose the forehead as the best choice for construction workers. Compared against other facial regions, the forehead is superior and more resistant to motion [5, p. 2]. Unlike the complex structure of the wrist, the forehead bone structure is more regular and provides a more even location to capture reflected light. Addressing wearability concerns, the forehead is a prime location because it does not affect the dexterity of the worker and can be easily integrated into existing headgear in a manner that is comfortable to the wearer [4], [11]. A design attached to the ear maybe uncomfortable or obtrusive, and stabilizing the ear during movement with an attached sensor mass would need to be addressed. The weight of the sensor or additional components adds little to the mass of the helmet whereas an ear-based design would need to clamp or hang from the ear and would likely become uncomfortable during the workday.

IV. Design of Helmet Prototype

We selected the Xpod pulse oximeter from Nonin utilizing a reflective sensor attachment. Marketed as an easy to use development kit, the Xpod is frequently used in prototypes that monitor from the forehead [4], [5], [10], [14]. The standard method for specifying pulse oximeter accuracy is as the root-mean-square (rms) accuracy between oximeter readings and reference arterial measurements [19]. For the Xpod and reflective sensor selected, the one sigma rms accuracy is ± 3 digits [20], indicating that the oximeter is accurate to 3 digits 68% of the time.



(a) (b)

Fig. 2. Interior (Xpod and reflective sensor) and back of prototype (Xbee radio and 9 V battery). (a) Interior view. (b) Back view.

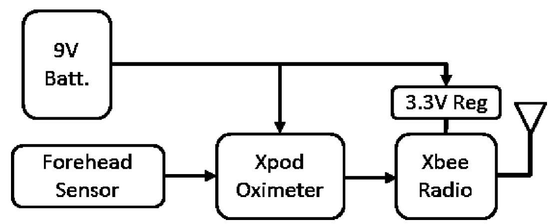


Fig. 3. Helmet schematic.

To enable wireless transmission of readings, the output of the Xpod was connected to an Xbee radio from Digi Inc. [21] that transmits the readings of the Xpod to a base station connected to a laptop. The final prototype is shown in Fig. 2(a), with the interior view showing the attached Xpod and sensor integrated into the headband. The back view in Fig. 2(b) shows the Xpod connection to the Xbee and 9 V alkaline battery. The connections between these devices are shown in Fig. 3.

A. Headband Design

In general, the design process was driven by a desire to shape the internal headband such that it minimized motion artifacts, and to place the electronics to reduce the impact of their weight. The headband insert shown in Fig. 2(a) was not the only form factor considered for the user study. An earlier design did not have the sensor surrounded by the foam insert, causing the sensor to easily slip out of place when the helmet was removed. The current design is a vinyl front with a foam backing that attaches to the existing helmet headband by Velcro. The oximetry sensor is recessed into the headband such that it is pressed against the forehead, but the extra foam padding softens the design and provides even pressure across the forehead.

The final design was a compromise between comfort and the desire to reduce motion artifacts, the main obstacle in helmet based monitoring. Since a reflective oximeter is required for use on the forehead, the sensor must remain still such that the backscattering reflections off the frontal bone are consistent over time. If the sensor moves relative to the forehead, motion errors are induced and a reading may not be possible. For reference, a normal PPG signal from the helmet prototype is shown in Fig. 1(a). In moving the helmet side to side, as if shaking the head "No," slight motion errors are induced in Fig. 1(b). However,, in Fig. 1(c), moving the helmet up and down, as if to nod "Yes," induces major errors and the signal becomes unusable. A major cause of motion is the torque moment applied by the helmet to the sensor. Because the sensor is physically integrated into the helmet, as it moves, so does the sensor and depending on the amplitude and frequency of movement, no measurement may be possible.

Several design iterations were conducted that attempted to isolate the sensor from helmet motion. Overall these attempts were unsuccessful because specific pressure is required at the measurement location to hold the sensor in place. This singular pressure point is extremely uncomfortable given that during typical wear the headband pressure is distributed evenly across the forehead. A better solution would be to mechanically isolate the internal assembly from the outer protective shell of the helmet. This strategy was used by Rhee in designing a ring sensor, by separating the internal sensors closest to the finger from the outer metal shell with only thin wires connecting the two parts [16]. Applying this method to the helmet, the internal assembly could be a simple elastic headband to which the sensor is integrated. The outer hard part of the helmet would still be attached, but such that it moves freely apart from the headband, much like the independent sections of a gyroscope. Additionally, accelerometers could be employed to help reduce the effect of motion artifacts [22], [23].

B. Electronic Design & Battery Lifetimes

The final prototype includes three major electronic components: the Xpod oximeter, the Xbee Zigbee radio, and a 9 V battery for power. The main connection point in the design is the break out board which holds the Xbee module. This board, purchased from SparkFun [24], allows direct access to the Xbee pins and provides a regulator that steps down the 9 V battery output to 3.3 V which supplies operating power for the Xbee. A schematic of the helmet design is shown in Fig. 3. The measurements from the Xpod are transmitted through the Xbee to another Xbee base station that is connected to a laptop via USB. This USB connection appears as virtual serial port and allows the Nonin oximetry software to run without modification.

Beyond the wearability requirements discussed in Section III, the helmet must have a battery lifetime that does not cause the worker to constantly replace batteries or switch out their helmet for newly charged ones. Currently, the lifetime of the prototype is only several hours when powered by a 9 V battery. The large energy drain is caused by the continuous transmission of measurements by the Xbee radio. In a deployed system, monitoring of the worker would be localized and power consumption could be much less. To enable local monitoring, a small microcontroller should be added to the system to monitor the oximetry readings. The Xbee radio would remain but would only be activated in case of an emergency where an alert was required. Additionally, the present design uses a simple linear power regulator, which could be replaced with a more power efficient switching regulator.

TABLE II
ESTIMATED SYSTEM LIFETIMES IN HOURS OF CURRENT AND FUTURE DEPLOYED DESIGNS

Design	I_{nom}	P_{nom}	9V Alkaline	9V Lithium
Current	91mA	303mW	15h	20h
Future	26.1mA	86mW	54h	76h

The lifetime of the system could be dramatically increased by modifying the helmet to transmit only during significant events or to sound an alarm, and implementing a new power regulator. The lifetimes of the current and future systems are estimated using typical alkaline[25] and lithium 9 V battery [26] in Table II. The microcontroller on the future deployed system is estimated with a PIC18 [27]. Additionally, the linear regulator would be replaced with a switching regulator to provide greater power efficiency. For the switching regulator, the system lifetime L_{switch} is given by (3), where V_{nom} and the P_{nom} are the nominal battery voltage and nominal system power, respectively. C_{nom} is the nominal battery charge capacity.

$$L_{\mathrm{switch}} \approx \frac{V_{\mathrm{nom}} C_{\mathrm{nom}}}{P_{\mathrm{nom}}}. \tag{3}$$

P_{nom} and V_{nom} are determined by the system configuration, however the charge capacity offered by the battery changes over time based on load and current draws. The information provided by the manufacturer in [25] and [26] does not allow for the charge capacity to be known at all times. To be fair in comparisons, for each battery type we used a nominal capacity that is the average capacity at a constant draw of 25 and 100 mA, which are the closest values to our two potential systems. The derived nominal capacity for the alkaline and lithium batteries are 550 and 762 mAh, respectively. The switching regulator was assumed to be 95% efficient.

The upper estimate in Table II provides an operation lifetime of 76 h, or roughly 9.6 days, in terms of 8 h workdays. As this product would be a critical safety device, the worker could simply replace the battery at the start of each week and be assured that the helmet will be powered for that entire workweek. Additionally, instead of constantly replacing the battery, the helmet could be charged nightly, either at home or at the work site, to maintain a fresh battery. Both methods, replacement and charging, have their advantages, however, they both show that with limited modifications the battery issues related to the helmet prototype can be easily resolved.

V. ESTABLISHING RELIABLE MEASUREMENT

Currently, there is no standard procedure for testing oximeters under motion. As mentioned in Section II-C, tests involving random hand motion or tapping have been performed, but those activities are not as strenuous as the motions expected in construction activities. Additionally, the ISO 9919:2005 standard that governs medical oximeters places the burden on manufacturers if their oximeter is claimed to work during motion [19]. For the Xpod used in the helmet, the manufacturer reports an error of ± 3 digits for $\mathrm{SpO_2}$ values during periods of motion including spikes, tremors, and movement [20]. However, the motions performed in our construction tests are more strenuous and prevent the oximeter from reporting $\mathrm{SpO_2}$ and heart rate values. Therefore, we must establish our own criteria for reliability of the oximeter during motion, which we outline in the remainder of this section. Section V-A describes the repairable systems model that was used to characterize the behavior of the helmet during motion. Section V-B describes our estimates of worker time to impairment and Section V-C outlines the user study that was conducted to test the reliability of the helmet.

A. Repairable Systems Model

To validate the performance of the helmet, we need to determine the reliability of the helmet to warn workers of impending carbon monoxide poisoning. The main obstacle to reliable monitoring is the interference of motion artifacts on the performance of the oximeter. However, the concern over motion artifacts is lessened by the knowledge that a worker will not be overcome immediately by carbon monoxide. Thus, the oximeter does not need to monitor the worker continuously, but only obtain a reliable measurement before the worker becomes impaired. This measurement can then be used to warn the worker or send out an alert.

For our study, we defined a motion artifact as an error that met one of the following conditions: 1) the presence of a warning flag indicating either out of track pulses, or the sensor is disconnected; 2) a "missing data" value reported for $\mathrm{SpO_2}$ or heart rate; and 3) reported $\mathrm{SpO_2}$ is $<95\%$. Conditions (1) and (2) indicate normal functionality of the oximeter, while (3) is a special case required due to ambient light contaminating the readings. It was found that during certain activities the helmet would report $\mathrm{SpO_2}$ values but because of the noisy signal, its values were obviously incorrect. In most cases the reported $\mathrm{SpO_2}$ would drop below 90% during heavy motion, which is not correct considering a user would be experiencing a serious health event at that level and no users were under strenuous exercise. A level of 95% approximates a typical oxygen saturation value.

A failure in monitoring can be expressed as a motion artifact that lasts longer than the time to impairment (T_i). In this situation, the oximeter would be unable to establish a reading before the worker becomes impaired. If the probability distribution of the motion artifact durations is known, then the probability that the duration of a motion artifact X is greater than the time to impairment T_i can be expressed by (4).

More formally, let $\mathbf{S}$ represent the state of the system which has two possible values, *uptime* and *repairtime*. The time during which the device is working properly is called *uptime*, and when the system fails, it immediately begins *repair time* and upon completing repairs is restored to *uptime*. The transition between these states is determined by the presence or absence of motion artifacts.

Let $\mathbf{X}$ represent a randomly distributed variable that describes the duration of repairtime. $P_X(x)$ is the probability that duration of repairtime will be x. If the system has some periodic deadline, T, that it must meet (in our case this is the time to impairment), then system will fail to meet its deadline if the duration of a repairtime is longer than T. The probability of this event is found by (4)

$$P_X(x \geq T). \tag{4}$$

For our prototype helmet, the times at which the helmet is giving proper readings will be considered uptime. When a motion artifact begins, the sensor will fail to provide a valid measurement and the helmet will be considered to be in repair time until a new valid measurement is received. The transition between these states is known because the oximeter provides error indicators to identify the quality of the measurement. This formulation of the duration of motion artifacts allows us to treat this as a *repairable system*, which is common in reliability analysis [28].

As no one has studied the distribution of motion artifacts in wearable systems, the probability distribution of our repairable system is initially unknown. However, the lognormal distribution is widely used to describe repairable processes. In previous works, Ananda [29], [30] used a two-parameter lognormal distribution for repair times while examining steady-state availability of systems. Schroeder and Gibson [31] examined several distributions to model high performance computing failures, finding that repair times were best modeled by a lognormal distribution. Also, software failure rates have been proposed to be distributed lognormally [32], and normal temperature distributions can cause lognormal failure rates in thin-film conductors [33].

From these examples we will assume a lognormal distribution to model our repairable system. Section VI-B validates this assumption by showing that the lognormal distribution can be accepted under χ^2 goodness of fit analysis, whereas other distributions, such as the Weibull, cannot be accepted. This distinction is important due to differences between the lognormal and Weibull when modeling heavily tailed data [34].

Under our assumption of a lognormal distribution, P can be replaced in (4) with the lognormal cumulative distribution function, F, giving (5)

$$P_X(x \geq T_i) = 1 - F_X(T_i; \mu, \sigma). \tag{5}$$

The parameters μ and σ are the shape parameters for the lognormal, where μ is the lognormal mean, and σ is the standard deviation. These parameters can be found empirically by observing the occurrence of motion artifacts over a typical set of activities. This was accomplished by performing a user study involving typical construction tasks, as described in Section V-C. As each user performed the activities, the results were recorded and examined to determine the distribution of motion artifacts. Thus, for a particular set of activities, it is possible to obtain an empirical estimate of artifact distributions, and find the probability of protecting the wearer. Given this model for the distribution of the duration of motion artifacts, we must next determine a conservative bound on the time to impairment.

TABLE III
PARAMETERS OF THE CFK EQUATION

V_{co} = endogenous CO production	V_B = blood volume (mL)
M = CO affinity for hemoglobin	P_CO_2 = capillary pressure of O_2 (mmHg)
$P_{I_{CO}}$ = inspired pressure of CO (mmHg)	P_B = barometric pressure (mmHg)
V_A = alveolar ventilation rate	P_{H_2O} = vapor pressure of water (mmHg)
$[COHb]$ = CO concentration (g/mL)	[HbO$_2$]=O_2 concentration (g/mL)
D_L = lung diffusivity (mL/(min*mmHg))	

B. Determining Time to Impairment

To establish a bound on how long a motion artifact can last while still providing warnings before a worker is overcome by CO poisoning, we must estimate the impairment time T_i for someone exposed to carbon monoxide. It is this limit which the distribution of artifacts is compared against to determine whether the helmet will be able to acquire a reading of the wearer before he/she becomes impaired. A conservative estimate is desirable because it establishes a lower bound on the time for T_i, providing assurance that if the most at-risk workers are protected, then healthy workers are safe as well.

This conservative estimate can be found by deriving physiological profiles of typical and at-risk workers and simulating their uptake of carbon monoxide under various levels of activity. The simulations of carbon monoxide uptake were performed using the CFK equation [35], which has been verified in several studies and gives an accurate assessment of CO uptake for various exposure levels, body sizes, and activity levels, [36]–[38]. The CFK equation is shown in (6) as expressed by [38]. Relevant physiological parameters are defined in Table III

$$\frac{d[COHb]}{dt} = \frac{\dot{V_{CO}}}{V_B} + \frac{1}{V_B\beta}\left(P_{I_{CO}} - \frac{[COHb]P_CO_2}{[HbO_2]M}\right). \quad (6)$$

Complexity is added to solving the CFK equation because [HbO2] is not constant but dependent on the current amount of [COHb], thus the equation becomes nonlinear and must be solved through numerical means. To compensate for this nonlinearity, Peterson *et al.* [37] used a trial and error method to converge on the proper value of [COHb], whereas numerical integration with RK4 was used by Bernard *et al.* [36] and Tikuisis *et al.* [38] with a small enough step size such that [HbO2] could be updated at each step. Both methods were implemented in this work and little difference was noted between the two solutions. Because RK4 is a more commonly known and accepted method, it was used for our analysis. During simulation a step size of .01 minutes was used.

To understand what level of coverage is required by the worker population, we must understand what factors affect carbon monoxide uptake the most. Looking at (6), this is not directly obvious, but when considering how CO enters, exits, and binds to the body the most important variables are clear. The build up of carbon monoxide within the body is directly related to how much is inhaled, exhaled, and how rapidly over that time period. The faster a person breathes the quicker CO will diffuse across the lungs. In cases of poisoning, when two equivalent people are exposed, the person who is breathing the most or working hardest will present advanced symptoms quicker, revealing that V_A is key in CO uptake.

TABLE IV
PROFILE OF TYPICAL AND AT-RISK WORKERS

Physiological Parameters	**Typical**	**At-Risk**
V_B(mL) [37]	5,500	5,000
[Hb] (g/100mL) [41]	15.71	13.0
Initial COHb (% Saturation)	5	5

TABLE V
RESPIRATORY EXERCISE PARAMETERS FOR VARIOUS INTENSITIES

	V_T (mL)	f	V_D (mL)	$\dot{V_A}$ (mL)
Resting	500	12	200	3600
Moderate	2,500	30	150	70,500
Intense	3,000	50	150	142,500

Similarly, the effects of CO poisoning become more severe as COHb increases relative to total blood count, thus those with high CO background levels, low hemoglobin counts, or small body size are at significantly greater risk when doing equivalent work. If two people are working at the same activity level, in the same exposure level, the one who is already a smoker, smaller, or suffering from anemia will be overcome in a much shorter timespan. Thus, background Hb and V_B values greatly influence the uptake of CO, in addition to V_A.

To measure how these variable affect a population, two profiles were created for typical and at-risk workers with each profile working at resting, moderate, and intense levels of activity. The two theoretical subjects were exposed at an extremely high concentration of 1200 ppm which is defined as Immediate Danger to Life and Health by NIOSH [3, p. 3], [39]. Also, recognizing the impact of activity level, resting, moderate and intense levels of activity were derived from exercise conditions in [40, p. 269]. The physiological profile of both workers in shown in Table IV.

The various levels of activity were derived from tidal volume (V_T), dead space (V_D), and breaths per minute (f) values given in [40] and converted to $\dot{V_A}$ measurements by (7). The resulting activity levels are shown in Table V

$$\dot{V_A} = f(V_T - V_D). \quad (7)$$

Fig. 4 shows the simulated % carboxyhemoglobin (COHb) saturation for typical and at-risk workers at resting, moderate, and intense levels of activity in an environment with a CO concentration of 1200 ppm. A person typically is considered to be impaired at 30% COHb saturation [7]. From Fig. 4, the shortest time to reach 30% COHb saturation is 11.6 mins, corresponding to an at-risk worker with an intense activity level.

C. User Study

A user study was conducted to validate the helmet prototype design. The study featured ten students performing six construction related tasks intended to mimic typical motions and actions of construction workers. The study was conducted in Torgersen Hall on the campus of Virginia Tech and was approved by the Virginia Tech Internal Review Board (IRB # 09-768).

As this is the first study to attempt to monitor workers in real-time, simple tasks and novice users were selected to assess

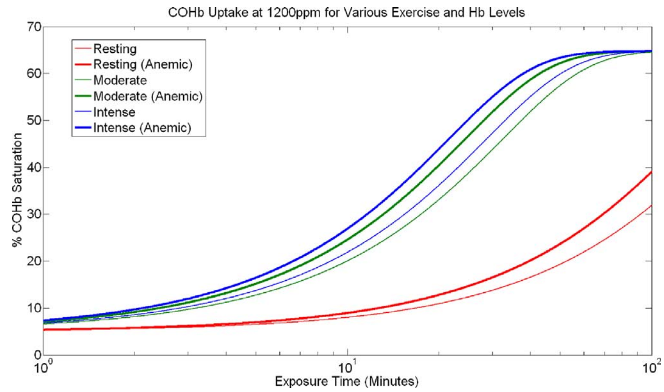


Fig. 4. Estimation of carbon monoxide uptake at 1200 ppm.

(a) (b) (c) (d) (e)

Fig. 5. User study activities. (a) Walking. (b) Stairs. (c) Sweeping. (d) Boxes. (e) Hammering.

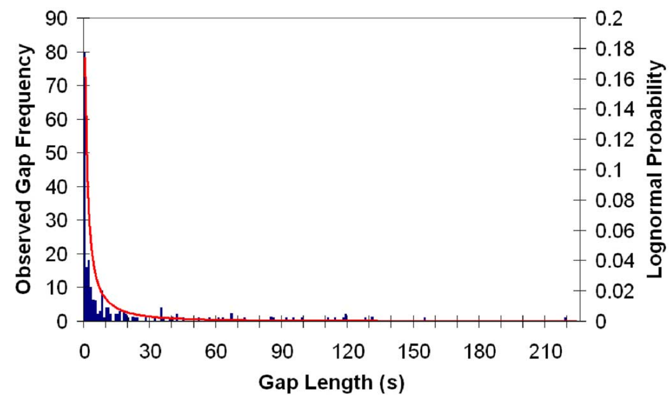


Fig. 6. Histogram fitted with lognormal distribution.

the feasibility of the prototype. While a full deployment of the helmet on an actual construction site would lend greater credibility to the reliability of the helmet, basic tests must first be performed to assure those advanced tests would be worthwhile. If the helmet cannot pass the basic tests and activities described below, then more involved testing is not necessary.

1) Task Selection: Six individual tasks were selected for the user study: walking, ascending/descending stairs, sweeping, moving boxes, and hammering paint cans. Each task sought to mimic the activities and motions of a construction worker without necessarily the impact or stress that performing the actual activity would cause. No standardized set of safety activities or motions was found. However, the selected activities are sufficient for judging the feasibility of the design. Simple tasks were specifically selected as this is a feasibility study and if the helmet cannot pass the simple tasks presented here, then it will not pass more rigorous ones later.

2) Participant Selection: Study participants were graduate and undergraduate students. Experienced workers in construction are not required because only the motions of tasks need to be approximated, not necessarily the task itself. A person does not need to be an expert hammerer to approximate the required hammering motion. Likewise, for the simple tasks selected, moving boxes, walking, or sweeping the inherent motions are assumed to be equivalent between experienced and non-experienced users.

3) Protocol: After placing the helmet on the user, the user was instructed to tighten the helmet to a comfortable fit. The fit of the helmet was adjusted manually if the user tighten or loosen too much, such that a good signal could be found. After fitting the helmet each user was instructed to walk around the third floor of building three times. This task is a baseline measurement of helmet performance; if the motion of walking is too great, then more advanced tasks are not feasible. After completing the walking circuit, the users were asked to walk down the stairs to the first floor twice and then return. Fig. 5(a) and (b) show the third floor of the building where these two tasks occurred.

A more involved motion was desired to ascertain the effects of upper body movement on the helmet. To approximate this motion, many pieces of paper were dumped on the floor and the user was asked to sweep up these items, this task was repeated three times. The user was not idle while performing this task and had to move around and sweep to complete the activity.

The final tasks were to have the users hammer on several paint cans and move boxes around a laboratory. These acts simulate the effects of hand tools on head motion and also the bending and lifting motions of carrying. Hammering was conducted with the cans both on the floor and on a saw horse. For the boxes task, each box was individually labeled and the users were asked to move them across a room and stack them in proper order. This task involved multiple motions of moving, bending, and lifting to accomplish.

The transmitted readings from the helmet were captured at the start of each activity and stored on the laptop in text files. Later, the files were parsed to reveal repair times based upon the conditions outlined in Section V-A.

VI. Results

A. Verifying Helmet Reliability

As described in Section V, the distribution of motion artifacts is critical to understanding the reliability of the helmet. The observed distribution of artifacts from the user study and the fitted lognormal distribution curve are shown in Fig. 6. The data presented here is the collected results of ten user trials. The x axis is the artifact duration in seconds, the left y axis is the observed frequency of each artifact occurring, and the right y axis is the probability of events associated with the lognormal distribution. The red line indicates the fitted lognormal distribution with parameters $\mu = 1.02$ and $\sigma = 2.03$, which closely fits the observed distribution of artifacts. Additionally, Table VI provides χ^2 metrics of fit for the lognormal distribution.

TABLE VI
METRICS OF DISTRIBUTION FIT TO HISTOGRAM

Distribution	$P(X \geq T_i/2)$	$P(X \geq T_i)$	χ^2 p-value
Lognormal	0.0091	0.0034	0.1785
Weibull	0.0013	$7.71E-5$	0.0349

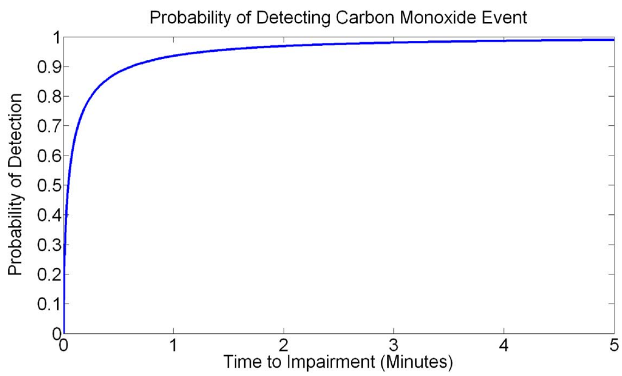


Fig. 7. Probability of detecting carbon monoxide event.

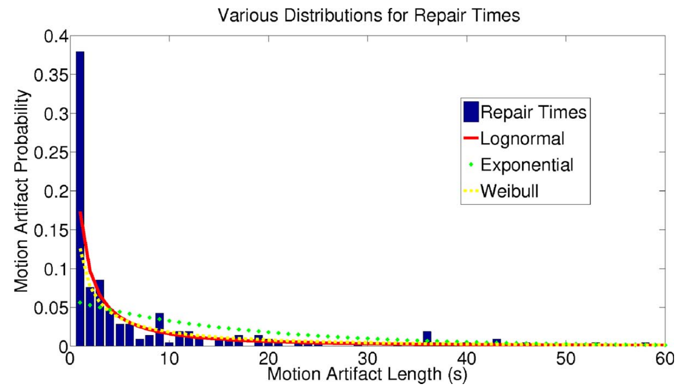


Fig. 8. Various distributions mapped to histogram.

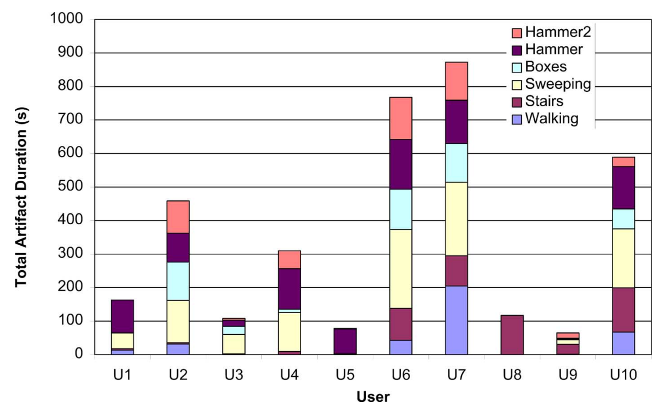


Fig. 9. Individual activity contribution to total artifact duration.

Assuming the same apply to CO oximetry, Fig. 7 shows the probability of detecting a carbon monoxide event as it varies with time to impairment (T_i), from (5). The probability of a measurement artifact occurring that is longer than $T_i = 11.6$ minutes is $p = 0.34\%$. This result shows how likely the prototype is to fail while monitoring a worker. Conversely, the probability the helmet will notify the worker is $1 - p$, or 99.66%.

While these are excellent results, given the way our objectives are constructed, it is possible a single measurement could occur near time zero and then the remaining time to T_i could be covered by an artifact. This situation would still be considered valid monitoring time, as the artifact would not be the full length of T_i. However, depending on how early the singular measurement occurs, it may not contain any useful information as internal carbon monoxide levels may not have risen to the level of concern.

To counter this possibility, we can conservatively divide T_i in half to create two new measurement intervals against which we will test the probability of measurement artifacts. While measurements from time 0 to $T_i/2$ may not reveal any carbon monoxide presence, at $T_i/2$ the internal COHb levels for our worst-case worker will be 17.5%, significantly above normal levels. Thus, any measurement in $[T_i/2 - T_i]$ will warn of the presence of CO. Replacing T_i with $T_i/2$ in (5), we find the probability of a artifact covering the new $T_i/2$ intervals (5.8 min) is $p = 0.0091$ or 0.91%. Conversely, this indicates the helmet will provide protect the worker with probability 99.09% in these more conservative intervals, giving a strong indication that the helmet will find a valid reading upon which to accurately warn the worker. Even if the time to impairment were reduced to 2 min, probability that the helmet will notify the worker would be greater than 96%.

B. Choice and Fit of Distribution

At times there is an ambiguity between selecting the lognormal or Weibull distribution [34]. The main concern is the impact of heavily tailed data on the overall result. This effect can be seen in Table VI where the values of $P(X \geq T_i/2)$ and $P(X \geq T_i)$ are shown. At $T_i/2$, the probabilities are on the same order, however when extrapolating to T_i the difference becomes two orders of magnitude.

We can be assured that the lognormal is the correct choice by the χ^2 p-value. At 5% significance, we can reject that the artifacts come from a Weibull distribution, but cannot reject they are from a lognormal distribution. Furthermore, Fig. 8 provides a visual indication of how well the distributions fit. The exponential distribution is also included because at times it is substituted for the lognormal for ease of computation [42]. The 95% confidence interval on μ is [0.74 , 1.84] and σ is [1.29 , 2.24].

C. Helmet Performance Factors

Fig. 9 shows the aggregate duration of motion artifacts for each user and activity performed. From the figure, it is clear that there is a range of performance in terms of how well the helmet monitored each participant.

Exploring the artifact duration results further, we would like to understand which factors, the users or the activities selected, influenced the overall results. Simply, are there activities that the helmet cannot monitor well, or are there certain users where the helmet does not work properly? If we organize total artifact information from Fig. 9 into a matrix of Users by Activities as in Table VII we can use Friedman's Test [43] to determine if the

TABLE VII
ORGANIZATION OF TOTAL ARTIFACT DURATION FOR FRIEDMAN ANALYSIS

	Walking	Stairs	Sweeping	Boxes	Hammer	Hammer2
U1	13.4	4.6	46.9	0	98.3	0
U2	31.7	3.9	126.3	114.3	86.4	95.8
U3	0.5	1.7	58.1	24.1	18.4	5.3
U4	0	9.5	116.0	10.2	120.8	53.6
U5	0	0	0	2.8	74.0	1.6
U6	42.9	95.4	234.8	120.7	147.9	126.3
U7	204.4	90.8	219.3	115.4	129.0	113.7
U8	0.5	116.3	0	0.2	0	0
U9	1.5	29.2	13.7	2.8	1.8	16.1
U10	67.1	132.0	176.4	59.6	126.3	28.0

TABLE VIII
RESULTS OF FRIEDMAN'S TEST

Source	**SS**	**df**	**MS**	χ^2	**Prob**$> \chi^2$
Columns	36.55	5	7.27	10.66	0.0586
Error	134.15	45	2.98		
Total	170.5	59			

activities (columns) have equal or non-equal effects on the total artifact duration.

If the activity effects are equal, then we can conclude that user effects have a greater impact on the total artifact duration. The results of the Friedman's test are shown in Table VIII. Assuming a null hypothesis H_0 that the activity effects are equal, Friedman's test gives a p-value of $p = 0.0586$ which at 5% significance ($\alpha = 0.05$) indicates we cannot reject H_0.

This result confirms that the effects of all the activities are statistically equal and the differences in total duration are a function of the users. From this we isolate two items that could explain the differences, the tightness of the helmet and conditions of the measurement site on the user's body.

The tightness of the helmet is a prime factor in how well the sensor performs. As Dresher found, there is an optimal sensor pressure at which a good pulse can be detected [4]. In our study, users were instructed to wear the helmet at their comfort level. Depending on their personal feel, they may have tightened the helmet too much or too little, moving away from an optimal pressure and degrading the result. Conditions of the measurement site may cause poor readings if there is not sufficient perfusion in the tissues to allow a reading. In particular, User 7 indicated that he had a scar on his forehead near the site where the sensor would normally sit. The scar may have damaged the vascular bed and restricted blood flow to the site. If true, this could be the cause for User 7 having the largest duration overall. The implications of poor measurement site conditions indicate that future designs may need multiple sensors inside the helmet or some method to permit sensors to move around.

VII. CONCLUSION AND FUTURE WORK

We have integrated a pulse oximeter into a typical construction helmet to assess the feasibility of monitoring for exposure to carbon monoxide. Ten participants took part in a user study to characterize the performance of the helmet using simulated construction tasks. For a time to impairment of 11.6 min, the helmet was found to be capable of warning the user before becoming impaired in 99.66% of cases. For further assurance, the time to impairment could be halved, with the helmet still providing a reading in 99.03% cases.

The promising results indicate a high reliability in monitoring, however, no protective system is perfect. We do not assert that the helmet is 99% reliable for all activities; in fact we believe there will be activities where no measurement is even possible, such as operating a jackhammer. However, with these basic but reasonable tasks, we have shown that it is feasible to conduct monitoring during typical construction tasks. Further work in isolating the sensor from helmet motion, and longer, more complex tasks will allow a greater understanding of the true abilities of the prototype. But as a proof-of-concept, the helmet verifies the idea of an integrated pulse oximeter for construction activities.

Finally, this helmet is only the first step toward our long term vision of having a network of wearable and environmental sensors and intelligent personal protective gear on construction sites that will improve safety for workers. While this helmet targets carbon monoxide poisoning, we believe there are compelling opportunities for wearable computing in reducing injuries and fatalities due to falls, electrocution, particulate inhalation, and workers on foot being struck by vehicles. Because a worker in an accident may be unable to self-rescue, the use of only a personal alert is not adequate. Thus, we envision a multimodal, site-wide alert system that automatically warns co-workers and supervisors of a person in danger. This system would transmit to summon distant help, or provide visual and audible cues to the location of the worker. Such a system must fit into the social expectations, existing daily routines, and physical constraints of a wide range of construction activities, sites, and environmental conditions. An intelligent construction site safety system would also improve existing capabilities for collecting data on accidents and near-accidents, which would in turn lead to improved analysis for preventing accidents.

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