A survey of wearable sensor networks in health and entertainment

Abstract

The world of wearable sensor networks is constantly improving as the potential benefits these systems offer become more apparent. Today, there are several wearable sensor networks being developed for health and wellness purposes as well as entertainment purposes. This paper will take a closer look at the different available sensors that are being used to collect data, as well as the systems that use them. Sensors for fall protection for the elderly, long-term health monitoring, human gait analysis, interactive media, and gaming and animation are studied with respect to the state of the art in wearable sensor technologies. This research hopes to further advance the technology for the wearable sensor networks and wearable health monitoring systems in these fields.

Introduction (Survey)

Wearable sensor technology is a growing field as more clinicians, researchers, and developers learn of the potential benefits and possibilities it offers. From athletes to the elderly, those with medical conditions or injuries will soon benefit from wearable technology if they have not done so already. Basic forms of wearable medical technology have already been made commercially available over the last couple of years. Examples of these include electronics or smart phone applications that encourage physical activity by measuring the user’s daily step count, but this is merely a taste of what’s to come. Wearable technology can also come in the form of a Wearable Sensor Network (WSN) also known as a wearable Body Sensor Network (BSN), or even a Wearable Health Monitoring System (WHMS). In a WSN, multiple sensors communicate to one another to form a network, and the more sensors used in a system, the greater the potential that system will have to offer. In the medical field, future WSNs will have the capability to capture data needed to diagnose serious medical problems with greater precision than that of current methods, and may even allow clinicians to find solutions where there previously were none. The entertainment industry will be impacted by WSNs as well. Both game developers and cinematographers have long used sensor networks to give animated characters complicated, yet organic motions, and these realistic motions have become expected from consumers of today’s media. Additionally, gamers desire a higher level of immersion in the games they play, as proven by the success of interactive virtual reality gear, and wearable sensors can only further add to that experience as more of their body motion can be captured and transferred into the virtual world. Wearable technology will allow for more affordable motion capture option for gamers, game developers, and cinematographers, in addition to offering greater freedom than that of conventional optical marker tracking systems. Sensor technology has improved such measuring devices such as electrodes, gyroscopes, and accelerometers are now affordable, lightweight, and compact. These attributes are required for wearable sensing systems as they generally must remain unobtrusive to the user. It is for the aforementioned reasons that WSNs are the obvious path to accurate, personalized healthcare, and for meeting the needs of today’s entertainment industry. These systems are likely to change the way in which the majority of clinical data is collected in the upcoming years. Unfortunately, much of the capabilities discussed have yet to be realized in a practical commercial form at the time of this document’s publication. However, progression towards advanced WSNs have been building for decades, and have been accelerating as more companies push to deliver useful products based upon the latest in sensing technology.

Background/history of wearable sensor networks/sensor types

The past ten years have shed much light on the development of WSNs, particularly those in the health and entertainment industries. There are many different sensors available to meet the needs of these industries. One of the most commonly used sensor types in WSNs is known as the Inertial Measurement Unit (IMU). This sensor collects gyroscope, magnetometer, and accelerometer data, and have been used extensively in the military for over 100 years. IMUs are presently available at the micro scale due to recent advancements in Micro electromechanical Systems (MEMS). When programmed properly, IMUs are capable of tracking their own kinematic motion. When attached to the limbs of a subject and, after being calibrated to that particular user, the IMU will be able to collect data of the user’s kinematics. If given a network of wearable IMU sensors, one can have a full human body motion captured in terms of kinematic data. The post processing of this acquired kinematic data changes from field to field depending upon its intended use. The entertainment industry for example is likely to desire a natural motion animation for a character in a game, movie or to solicit interactive feedback at a dance performance. The medical and health industry, on the other hand, is likely to desire a comparative plot between healthy and unhealthy motion behavior. One unfortunate drawback experienced by IMUs is their tendency to experience what is commonly referred to as “drift” where the sensor becomes misaligned over time, and eventually requires the user to recalibrate the system to resume accurate data collection. This effect is worsened when a gyroscope is used, and encounters an external magnetic field. External magnetic fields can easily throw off the calibration of an IMU that relies heavily
on data from the gyroscope, and it is for this reason, and the fact that the gyroscope consumes a large amount of energy, that software techniques are often used to minimize use of gyroscopes in motion capture data collection. Despite its flaws, the IMU is an extremely useful sensor to have for many purposes, but other sensors have also been used in WSNs, such as the electrode. An electrode is a small conductive piece of material, usually metallic or gel, which collects data while attached to the user’s skin. Electrodes are capable of noninvasively measuring Surface Electromyography (sEMG), as well as electrocardiogram (ECG). sEMG and ECG measurements are how clinicians measure one’s muscle activity and heartbeat, respectively.6 Other sensors have been included in WSNs such as flexible sensors that measure joint flexion through deformation of a special materials. Respiratory rate, blood oxygen content level, ground reaction force, blood temperature, and skin temperature are all quantities than can be measured with sensors small enough to be added to a WSN or WHMS.4,5 Additional sensor types include those developed for use in e-textiles, which will be discussed in detail, below, and the list of available sensors applicable for BSNs is growing.

**Activity recognition/fall prevention**

A growing need for wearable sensor networks, and wearable health monitoring systems is the ability to accurately identify and classify the action of the wearer based upon the combination of joint motions and sensor signals.13 This is known as the activity recognition, where methodology similar to that of the Hidden Markov Model (HMM) is used to identify the future unknown actions of a person based upon a number of known parameters.21,22 Activity recognition has an enormous potential in WSNs used for health or motion detection purposes. Activity recognition is the basis for more advanced applications such as advanced embedded decision support, which would allow a WHMS to perform proper statistical and intelligent processing of multiple bio-signals. This processing of signals can be referenced against a series of pre-defined “medical rules” that could lead to on-site incident detection. Activity recognitions currently being analyzed in the context of fall recognition for the elderly.2 Due to advancements in medicine, the average human life expectancy has been on the rise.4 Activity monitoring and fall prevention are two significant concerns for the world’s elderly population. In order to retain the independence and well-being of elderly people, systems such as the one described by Freitas et al.,3 are being developed to allow elderly people to live independent lives, but still allow them to receive immediate care in the event of a fall.3 Freitas et al.,3 describes the development of a WHMS with a single IMU capable of monitoring the user’s kinematics for fall detection.

Other systems use multiple sensors to perform this task, such as that shown in Figure 1.7 The multi-sensor system tracks the user’s heart and respiratory rate additionally to track their overall health status.7 Most of these systems will work by first having the user fill in some information regarding their personal contact, and the contact information of those who would come to the user’s aid.8 Next, the user wears a sensor, which can be integrated into clothes or strapped to the body.9,10 If the sensor identifies a problem, the WSN will send an alert to the user’s phone via a Short Message Service (SMS) that will allow the user to cancel the alert within 30 seconds in the case of a false positive.9,10 If the user does not cancel the message within the allotted 30 seconds, the alert will be assumed unconscious, and the contacts of those listed as aids will be notified to assist the user immediately. The biggest drawback of such a system is the occurrence of false positives. False positives occur when the user has not fallen, but the sensor(s) have moved in such a way that the sensor is tricked into positively identifying a fall. In the previously described system, if the user does not cancel the warning message they receive on their phone within 30 seconds, valuable resources and time may be wasted trying to come to the aid of someone who is not in need. The study by Freitas et al.,3 claims to have validated their sensor with different fall types, and the Activities of Daily Living (ADL) such as walking, running, sitting, and standing. They claim to have received no false positives, and no undetected falls.3 It should be noted that their system has not explicitly been tested at a large scale as of yet, so it cannot be said that false positives have truly been filtered out.4 Additionally, such a product needs to be accepted by the target community, and this may prove to be more challenging than those developing this system may have anticipated. One large flaw of the system is its dependency on the operation of the user’s cellular device.7 The system will not work if the phone is damaged in the fall as the phone is a critical component of the system. Additionally, elderly users may not be technically savvy, and yet such a system relies on them keeping their cellular devices charged, with them at all times, and set to alert them with a noise or vibration they’ll be able to detect. There is a real likelihood that false positives may occur due to users having their phone’s notification on silent, or them simply not hearing it in time to stop the alert. If such a false occurrence were to happen frequently, it is highly likely that users will grow frustrated with their fall protection systems, or fail to have the system ready when an incident occurs. These risks could potentially be mitigated with the addition of an independent measure of the user’s activities. The option of using in-home robots to monitor subjects is a potential solution as the robot could employ an entirely different measurement of fall detection which would drastically reduce the likelihood of encountering false positives.4 Such robots could be available to perform simple routine inspections and checkups if needed. Home monitoring camera systems have been investigated as well, but are potentially more invasive and more expensive than a simple robotic solution.

**Figure 1 Detection.**

**Wearable sensing in activity monitoring/energy expenditure estimation**

According to the World Health Organization, obesity worldwide has more than doubled since 1980.13 In 2014, more than 1.9 billion adults were overweight, 600 million of which were obese.14 Traditional measuring methods such physical activity monitoring through observation, are simply too expensive to be used on large populations, over long periods of time.3 Luckily, progress has been made in determining the energy one uses throughout the day through the use of IMUs and activity recognition algorithms. Phone applications and other small wearable devices are currently available.
that use these tools to help users track his or her daily activity level, and encourage a healthy amount of physical activity. These products were designed to assist those who suffer from obesity, type II diabetes, and cardiovascular diseases caused by, among other factors, a lack of exercise. However, these applications are significantly limited in their ability to accurately measure activities of the user as they only contain the equivalent of one IMU. The article by Dong et al. claims to have analyzed and compared the results of a single sensor system, and a multi-sensor network that were both used to track the energy expenditure of its user. Their article found that the system with more sensors was able to accurately measure the user’s energy expended. Clinicians desire more accurate and quantifiable activity information to provide useful feedback on metabolic energy expenditure, and for greater accuracy, additional sensors will be needed. In the article by Dong et al. an activity monitoring system is described that has been trained to identify 14 activities including lying down, running, sitting reclined, sitting up straight, standing, walking, jogging, riding a bike, and squatting.

The system uses a total of 3 IMUs which are attached with elastic straps to one of the user’s wrist, ankle, and thigh as seen in Figure 2. This was done as it was determined that these three locations are the “most important for high accuracy” in terms of activity recognition. This system was tested on only 10 people however, but was tested on half men and half women, and all subjects were between 22 and 30 years of age. Additionally, each subject was tested on four occasions and participated in 14 different activities, which took about two minutes per activity. The results of this testing showed over 90% activity detection accuracy for most of the subjects. The system has a range of roughly 50 meters, and connects wirelessly to an access point that is connected to a computer. Each sensor has a volume of 28.2 cubic centimeters, and weight 20 grams without a battery. The batteries used weigh an additional 13 grams and are claimed to operate the sensor for over 30 hours, but that is with a low data sampling rate of only 10 Hz, which may be insufficient for other motion analysis applications. Future goals for this activity monitoring systems are to develop further applications, and possibly incorporating an eating detection system.

![Figure 2: Wearable sensor network for activity analysis.](image)

Wearable sensing in long-term health monitoring

Out-of-hospital sensing systems are being developed for monitoring user parameters remotely, which will give a more personalized approach to health care management, and allow for additional freedom and comfort to those that would otherwise be confined to a hospital. Additionally, those suffering from diseases such as Parkinson’s, chronic obstructive pulmonary disease and epilepsy will benefit immensely from wearable sensor technology. Sensors embedded into a user’s home furnishings to collect data unobtrusively have been investigated, but only offer a visual data on patient behavior where more is desired. A long term WHMS is ideal for chronic diseases as they require near constant monitoring in order to appropriately analyze a patient’s status, and determine the requirements. The Mercury WSN platform was primarily designed for those who suffer from epilepsy, and Parkinson’s disease. Mercury is a sensor platform that provides clinicians and researchers with a high-level programming interface which makes developing policies for data connection and sensor tuning easier. The goal of the Mercury sensor platform was to support an emerging class of low-power wearable sensor platforms form medical monitoring. Mercury is capable of handling data on up to 8 nodes for a period of at least 24 hours. Although the Mercury system does not only work with the SHIMMER wearable sensor platform, the Mercury system does need to be paired with a device such as a SHIMMER that records the actual data collection. Mercury also implements feature extraction and other energy saving techniques in order to prolong the life of the data collection device. The SHIMMER sensor platform used in conjunction with the Mercury system weighs only ten grams, and has an area less than ten square centimeters making it more ideal for use as a long-term wearable device compared to larger sensing devices, although the thickness of the device was not given. Other systems have been examined, but are either too bulky, or not long lasting enough to have warranted testing with the Mercury system. The Mercury system currently requires the use of an external base station that is responsible for coordinating the sensor network’s operation and manages data sampling rates, acquisition and storage of data. In the future, the makers of Mercury hope to further reduce the data collected to reduce the needed battery size even further, and also to eliminate the need of an external base station in favor of a wearable base station such as a cell phone or iMote2. The ZigBee WSN has goals similar to that of the Mercury sensor platform, but differ in that the ZigBee system included hardware. The ZigBee WSN contains a network of IMUs that are also equipped with sEMG sensor nodes which provide useful muscle progression data for rehabilitation. This system was primarily designed to assist users in post-stroke rehabilitation, and also primarily focused on the upper body of patients as treatment and intervention are primarily focused on lower limbs. The report claims that the system would be ideal for providing visual feedback for patients in rehabilitation robotics, as well as a useful and simple diagnostic tool. It’s also suggested that this system may be suitable for lower body assessment, but it doesn’t mention what changes would need to be made to allow that to happen. The ZigBee WSN, similar to many other WSNs, has been validated through comparison with an optical tracking system, but that validation has only been done in upper body tests. The article states that no data packets lost during these tests, but the extent of the verification testing was not discussed in detail. Systems designed for long-term monitoring can be quite challenging from an engineering standpoint. These systems are required to operate for extended periods of time, and the longer a patient is required to wear a WSN, or WHMS, the more comfortable it ought to be, but the more energy it will require. The issue of keeping battery size down for such a system has led to many potential solutions that are currently being developed. One method to keep battery size down is to simply record less data by selectively choosing what is recorded based upon activity recognition.
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Walking is a highly complex motion, and for most people, is their most important daily action. Being able to predict an abnormal walking pattern is therefore very important.\textsuperscript{19} Human walking can be broken into repetitive patterns commonly referred to as gait phases.\textsuperscript{19}

The two primary phases are the stance phase, and the swing phase.\textsuperscript{19} The stance phase contains within it: heel strike, loading response, mid-stance, and the terminal stance, where the stance phase ends.\textsuperscript{19} The Swing phase consists of: pre-swing, initial swing, mid-swing, and terminal swing, upon which a single gait cycle ends, and the next may begin.\textsuperscript{19} This process can be best understood through the graphic in Figure 3.\textsuperscript{19} This complicated motion can be captured using visual motion capture systems, but can also be captured using IMU sensors in a WSN.\textsuperscript{19} Gait analysis requires sensors capable of measuring body joint angles, joint angular velocities, ground reaction force, and center of plantar pressure of each foot.\textsuperscript{19} The article by Chelius et al.,\textsuperscript{21} describes a system designed to perform long-term data recording in an outdoor setting, and its testing in the “Sultan Marathon des Sables” desert race.\textsuperscript{21}

This was done for a six-day competition and featured three types of sensors. Eleven motion-sensing nodes were used, one for every body extremity excluding the head and hands. The second sensor included six pressure-sensing nodes in each shoe insole as can be seen in Figure 4.\textsuperscript{21} Lastly, a master node was worn on a backpack shoulder strap, and was responsible for providing time stamps for the slave nodes to ensure all captured data is synchronized and also monitoring environmental conditions such as the humidity, altitude and temperature. Motion sensors were places on bony areas of the body to avoid muscle behavior reducing angle measurement accuracy, and compression sleeves were used around each one to ensure minimal movement relative to the body. Unfortunately, the system suffered from various technical problems, the biggest of which caused by poor quality electrical connections between the sensors and their batteries. For this reason, only a fraction of the event’s data was properly recorded. In spite of this, the study considered the event a success, and claimed that the system did not have any impact on the runner, despite the system weighing 150grams without accounting for the battery weight, and the runner using two 1.2Ah batteries per sensor node.\textsuperscript{21} The study also failed to offer any supporting evidence that would suggest such an additional load had gone unnoticed. The system’s creators are confident that simply improving the robustness of their interconnections will remedy the primary cause of their system’s shortcomings during this desert test. Article\textsuperscript{12} discusses an in-shoe pressure mapping system that is used to perform and identify the gait phases. These measurements are combined with machine learning techniques to outline the problem areas in a user’s gait.\textsuperscript{19} The algorithms developed by Novak et al.,\textsuperscript{20} segments the gait cycle into manageable and recognizable sections. The results of the study show the algorithm determining the beginning and end of the gait cycle with an 80% level of accuracy. Testing results were collected from a total of forty tests from only ten male subjects however, and their gait was measured while walking from one end of a room to another. The exact distance walked during these tests was not provided however. The maximum expected error of the IMUs in the system was three degrees, and the study concluded that the gait initiation detection algorithm can effectively predict gait initiation, but can only detect gait termination once said step is already in progress. The study also noted that IMUs are superior for gait termination detection, but insoles are better with gait segmentation. The algorithms developed are potentially ideal for prosthetics, exoskeletons, and other assistive devices.

The approach presented by Wentink et al.,\textsuperscript{21} is different from traditional gait analysis as it discusses gait analysis for transfemoral amputees.\textsuperscript{21} The gait cycle for a transfemoral amputee is different from that of a non-amputee, but research into the differences may be useful in both gait analysis, and control of active prosthetics. Went ink et al. concluded that EMG measurements taken at the prosthetic leg can be used in the prediction of gait initiation, potentially aiding in smoother walking for amputees.\textsuperscript{21} Disappointingly, this system was found to be unsuitable for heel-off detection or Initial Contact (IC) detection in the Prosthetic Leg Lead (PLL) condition due to what is most likely the weight balance of amputees, and their tendency to place more of their weight over their intact leg rather than their prosthetic. This causes the...
foot pressure systems that are used to measure the user’s GRF are not sufficiently triggered.

Figure 4 Inertial and force-sensitive (FSR) sensors shoe integration.

Wearable gait analysis systems are soon going to be of great benefit to the world of professional athletes as there has long been a need for wearable sensors to analyze physical performance characteristics, especially in the context of injury recovery. When an athlete or sports player is injured, they must take time off from their sport or training to allow their body to heal. Athletes and sports players are incentivized to go back to work as soon as possible after an injury, but if their injury has not fully healed, the likelihood of them being re-injured is greatly increased. For this reason, wearable sensors are needed to give professionals accurate information regarding the status of an injury, and can give a quantitative value to injury recovery progression. One such system is being developed specifically such that it can be worn underwater for use in hidrocinesiotherapy will be capable of measuring posture, heart rate, respiratory rate, and subject temperature. According to Rocha et al., their sensor is expected to be accurate to within three degrees, however little is mentioned in regard to specifics in how the system will achieve these goals. The article notes that only one sensor module was used in testing to demonstrate the feasibility of their system. Another issue with the system described is that their motion detection fails when given purely rotation over the magnetic field vector (earth’s magnetic field vector) meaning if the IMU is rotated while stationary, the IMU will fail to keep track of this motion, and the system may need to be recalibrated. E-textiles are being researched and developed with expectations to incorporate these sensors into fabrics that can be worn instead of attached. The Life Shirt from Vinometrics, and the Smart Shirt from Sensate are both currently available products which utilize conductive materials and fabrics to record data in a comfortable and non-intrusive manner. The flexible wearable sensor network (WeaSN) contains IMU sensors and electrodes that are sewn into the material with conductive fibers as shown in Figure 5. This WSN is equipped with both (sEMG) and (ECG) measuring electrodes, as well as IMUs. The sensors transmit the data through the conductive yarn traces to a Central Processing Module (CPM), and from there is then sent via Bluetooth link to the user’s phone or computer. Conductive yarn is used instead of traditional wires as user comfort is an important requirement for any body-worn WSN. It is not known however if such a system can be easily made to cope with issues such as conductive moisture contacting the sensors/data transmission fibers. The exposed nature of conductive fibers means that the integrity of the data signal may be compromised if the subject wearing the system comes in contact any conductive material, the most likely being rain water or sweat. Additional examples of e-textile systems under development can be seen in Figure 6. Flexible wired and wireless sensors are being developed that can change their resistance in association to the amount of stretching the material undergoes. Flatau et al., refers to these sensors as Smart Fabric Sensors (SFS’s) and defines them as “fabrics which are imbued with sensing properties”. SFS’s are a more generalized category of what are called Smart Fabric Transducers (SFT’s) which are fabrics that have been treated or modified in such a way that they are sensitive to temperature changes, electrical current, pressure, or force, all while remaining a flexible and form-fitting for a potential user. Flatau et al., also discusses how SFT’s can be used as power generators for harvesting energy from the user to prolong the life of a WSN, or as an actuator to assist the motion of a user.

Figure 5 “Examples of e-textile technologies developed over the past ten years. (A) A system developed by Wade and Asada relying upon special buttons that carry sensor technology to record physiological and movement data. (B) A system developed by De Rossi’s research team for monitoring the movements of the shoulder and elbow via recordings of the voltage drop on conductive elastomers that are printed on the garment.”

Figure 6 e-Legging: (A) Photograph of the prototype; (B) Diagram of the interconnections.
Wearable sensor networks in interactive media, computer animation & gaming

The paper by Park et al., discusses the design of a wireless sensor platform specifically for use in interactive dance performances. In an interactive dance environment, a live dancer’s movement is used to steer the synthesis of music and special effects in real-time. The system described provides a real-time and interactive environment between performance dancers and stage equipment using a small low-power node called Eco. The Eco sensor node has a volume of 7.2 square centimeters which the article claims is four to five times smaller than any other wireless sensor node in operation at the time of the publication (2006), and weighs just 1.3 grams without a battery. The article notes that these dimensions and weights are from the original Eco unit however, and that modifications were made to increase its functionality and battery size, so its final weight and size are larger depending on the size of battery fitted, which will control how long the system will be able to function between charges. The system claims to have improved an actual interactive dance performance, and hopes to have the system used in future performances on at least ten dancers together at once. The article also suggests the system being setup to display the heartbeats and body temperatures of the dancers in the form of colors to reflect the dancers’ conditions on the stage equipment. Any system designed to be used in gaming, or interactive media must be capable of providing immediate feedback for multiple dancers or players, which can pose a great engineering challenge as the bandwidth limitations make reliable data capture difficult. The WSN from Aylward et al., was designed to meet such a challenge, specifically for those in the dancing profession, and includes 4 IMUs per individual, where one IMU is located at each hand and foot of the user. The system was designed to be capable of collecting the data of 30 users in unison. The testing of this system was done on only 3 users however, and was done only to compare data from very basic arm motions. Additionally, each sensor node has a footprint of nearly 20 square centimeters without including the required antenna or external lithium polymer battery, and the thickness wasn’t mentioned. The range of their sensors was found to be around 15 meters, which may cause data loss if the dance environment is any longer than 15 meters from the receiver’s location. The system’s developers remark on future plans such as adding the ability to recognize certain gestures using activity recognition, and to help dancers in synchronizing dance ensembles as the outputs of the motions are averaged, and those who stray furthest from that average can be identified. In the gaming world, motion-based technology has become increasingly prevalent.

Optical tracking systems are often used in the computer-animation and film industries due to their high accuracy, but they offer minimal convenience at a high cost. WSNs can provide similar data to that of an optical system, but offer greater convenience at a fraction of the cost. One popular commercial WSN know as the Perception Neuron is capable of capturing full-body kinematic motion including wrist and finger motion with up to 32 sensors placed around the user’s body in a wired system of IMUs. The system boasts its lightweight and portable nature, although no battery pack is supplied, rather an external battery pack must be sourced elsewhere, and used to power the suit’s receiver. The Perception Neuron has been assisting game developers in generating useful motion animations since its successful Kickstarter campaign in 2014 where over half a million dollars was raised to create the system. Another similar system created by X sense is currently growing as well, but lacks the ability to track finger motion. X sense has developed a wireless motion capture system called Move that allows for actors to wear gear during capture sessions, which in turn allows for even more realistic motions than optical systems are capable of. In the context of gaming, one US patent was recently issued that described a plurality of IMUs being warn to capture a gamer’s body movement, and provide haptic feedback in the form of vibration motors and LEDs. The market trend for WSNs is for them to be integrated into a wearable motion capture suit. Having a WSN capture motion for gaming would expand a game’s ability to be interactive, and would offer gamers a more complete virtual reality experience that verges on augmented reality. Image-based motion capture systems use computer vision techniques to obtain kinematic motion data from a user without use of special markers, but these systems are less accurate than systems that use reflective markers, and those that require markers are not suitable for gaming due to their immense cost and processing requirements. WSNs made for gaming still have limitations however, as most gamers can’t simply run, kick and jump around their homes without incurring some amount of risk with varying consequences, and yet these motions are a big part of what games that would hope to use this technology for. Solutions for this problem are under development, but the solutions proposed are liable to increase the cost of gaming beyond what consumers are willing to spend. Challenges aside, wearable sensor technology is making its way into the entertainment world. Additionally, there are programs such as Signal Processing in Node Environment (SPINE) are being developed to help reduce development time for programs and applications that will use sensory data from WSNs or BSNS. Although SPINE is primarily focused as a framework for the development of BSN applications involving health monitoring and fitness, there will likely be similar frameworks being made to assist game developers and film producers with BSN integration as well. With frameworks making development faster and easier, the number of applications is bound to increase swiftly over the years to come.

Discussion, future work and conclusion

The world of wearable sensors and WSNs is growing, and the opportunities presented by this technology are undeniable. Added benefits to the entertainment industry and arts are welcome, but perhaps the most important use of this technology will be the medical field as it expands the capabilities of today’s health care system to meet tomorrow’s needs. Although many of the systems mentioned are in beginning phases of development, these new and developing WSNs hope to provide lifesaving data, and assist users in achieving their goals in a growing number of fields. With new machine learning algorithms being created to classify human activities, and new energy saving techniques, future WSNs are likely to become smaller and more powerful than ever before. The issue with many of these studies is the minimal amount of testing done. Ideally, studies on wearable sensors or health monitoring systems should make sufficient testing a priority to derive realistic results, and should include testing on large numbers of people of diverse backgrounds and age groups, unless said article’s goal is to analyze a distinct group of individuals in tackling relevant problems experienced by that group. Some issues stem from the article’s failure to mention any plan of action on tackling real issues with the system being tested. Many articles have claimed that simple fixes related to the functionality or compactness of the system will resolve any dilemmas, but there is much more to creating a WSN capable of reaching the goals set forth in the real world. Regardless, steps are being taken towards improved implementation of working WSNs and WHMS, it is only a matter of time before they’ll be in the hands of users around the world.

Citation: Olson JS, Redkar S. A survey of wearable sensor networks in health and entertainment. MOJ App Bio Biomch. 2018;2(5):280–287. DOI: 10.15406/mojabb.2018.02.00082
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Acknowledgements

None.

Conflict of interest

The author declares no conflict of interest.

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Citation: Olson JS, Redkar S. A survey of wearable sensor networks in health and entertainment. M0J App Bio Biomech. 2018;2(5):280–287.
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