Development of a Smart Insole Tracking System for Physical Therapy and Athletics

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ABSTRACT
Development of a smart insole tracking system is described. Originally designed for healthcare applications, the system has found applications in both physical therapy and athletic training. The entire system is distributed between insole hardware, mobile device applications that interface with the insoles and a central Internet server for data warehousing and analysis. We describe the development of these components so far including a discussion of custom algorithm development required for the system. The athletic version has been commercialized while the more complex healthcare version is still under development.

Categories and Subject Descriptors
C.1.3 [**Computer Systems Organization**]: Other Architecture Styles [**Heterogeneous (hybrid) systems**]

General Terms
Algorithms, Human Factors, Measurement.

Keywords
Physical therapy, sensors, tracking, mobile applications.

1. INTRODUCTION
In 2008, after an extensive knee surgery, MedHab® LLC founder and CEO Johnny Ross Jr., felt that some of the rehabilitation techniques used at the time were ineffective and inefficient. The idea for a digital sensor-enabled smart shoe insert was born. The original purpose of the system was to automate and enhance physical therapy. A patent application was approved in 2011 for a smart insole named StepRite®. To date, two patents have been approved and seven more are pending. In 2012, after a year of product development, it became clear the computer enhanced insole had applications in the athletic market as well as medical. The product line and corresponding development split into two separate paths. The medical version remained known as the StepRite® system while the athletic version was named RPM²®, shorthand for Remote Performance Measurement and Monitoring [2]. Both systems utilize the same insole hardware, shown in Figure 1. We describe the system and provide insights into the development of the two products including a discussion of significant design issues including the need for custom mobile applications and algorithm design.

Figure 1. Bottom and side views of StepRite® insole.

The product development workload has been divided between several entities. Texas-based Deaton Engineering provided the bulk of hardware design and development including the insole itself. Process and design engineering firm TMAC, also in Texas, developed algorithms for gait analysis. TMAC also created custom hardware verification devices for quality assurance. Faculty and students at Angelo State University and Lamar University were brought in to develop the bulk of the software including mobile applications, cloud server and algorithms for range-of-motion exercises. To validate the system, professionals in the field of both medicine and athletics, including physicians,

PETRA'14, May 27-30, 2014, Island of Rhodes, Greece.

physical therapists, and athletic trainers have provided feedback on the design and development of the system components.

2. DESIGN GOALS

In terms of the original goals for StepRite® as a medical device, it is a wireless, remote monitoring, force sensing device, designed to monitor rehabilitation of patients recovering from injuries and/or surgeries that impact the ability to stand or walk. The StepRite® system can also be used as a diagnostic tool, allowing the provider to assess abnormalities in gait and range of motion prior to surgery. The device measures force distribution by virtue of four force sensors embedded in shoe inserts. A 9-axis sensor is embedded in a microcontroller in each insert, creating a gyroscope, allowing for range of motion measurements of the lower extremities.

The device offers wireless communication and a secured user interface through mobile phone applications. While patients are exercising, data is collected wirelessly and uploaded to a HIPAA secured server, where the raw data is translated into charts and graphs. Through the use of the HIPAA secured server, healthcare providers are able to access information about the progress their patients are making with the rehabilitation protocol. Additionally, healthcare providers can modify the rehabilitation protocol at any time through the server, and the resulting changes are automatically and wirelessly transmitted to their patient's phone.

The StepRite® system has the potential to greatly impact the manner in which healthcare providers manage their patients. First, while rehabilitation exercises can be performed in the clinic under direct observation by the healthcare provider, they can also be performed in the comfort of the patient's home. Remote transmission of data affords the provider the most current information regarding the patient's progress or lack thereof and allows for ease of making modifications to the rehabilitation protocol. Second, given the duration of time that normally is involved in rehabilitation, post-orthopedic surgery, compliance to a rehabilitation protocol can be enhanced through remote technology. Access to patient data is facilitated through the HIPAA secured website and provides current information regarding compliance to exercise regimen, including type of exercise performed, number of times per day exercises were performed, and the number of repetitions and sets performed. Importantly, since all exercises are performed by both the injured and the non-injured leg, the StepRite® system provides the means by which measurements can be evaluated to ascertain return to function. Third, while rehabilitation therapy is critical for patients in terms of return to function post-procedure, there is significant cost associated with this process. While most insurance carriers allow for benefit payments for rehabilitation, the process is not always successful within the allotted time frame. Consequently, barriers to extension of the rehabilitation time frame might include the provision of justification to plan providers by healthcare professionals. In the absence of objective measurements of progress being made by the patient who is undergoing rehabilitation, it might be difficult obtaining the extension of services. With the StepRite® system, objective measurements are available and may provide substantive support for the extension of services. Finally, the StepRite® system, given remote technology features which enhance the patient-provider continuum, patients have increased chance of augmenting the rate by which rehabilitation occurs and may get better, faster.

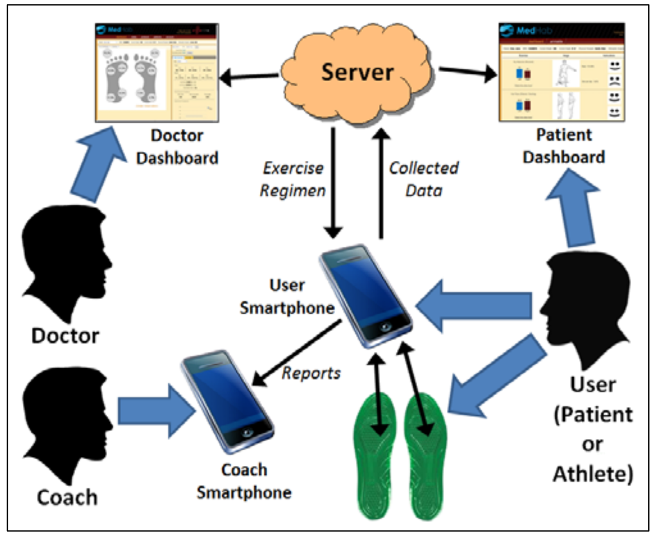

Figure 2. Combined system architecture showing both medical and athletic versions.

3. SYSTEM ARCHITECTURE

The combined system architecture for both the medical and athletic versions of the system is shown in Figure 2. The core technology is the computer-enhanced insoles. The insoles can be ordered in six sizes and the edges can be trimmed to conform to the inside of a shoe. Several iterations of materials were tested during pre-manufacturing to find a combination of material that was sturdy enough to house the electronic components and prevent them from being damaged while at the same time exhibiting a degree of comfort for the user. The user - patient or athlete, does not interact directly with the insoles except for charging the batteries which in typical usage last approximately six hours per charge. Early in development a dedicated Bluetooth-enabled data receiver was envisioned to collect data from the insoles. This was abandoned after it was realized that smartphone technology would be sufficient for the task. The insoles and smartphone application communicate via a secure wireless Bluetooth connection. The primary interface for the user is the smartphone application. Two different applications have been developed – one for the medical user and another for the athletic market.

The medical version of the system utilizes a cloud server. The physician selects, edits, and monitors the patient's exercise regimen from a set of approximately 100 exercises. This regimen is downloaded to the smartphone on each connection to the server. After each exercise is recorded the data is transmitted via secure-HTTP protocol to the server for archival and analysis. Physicians and their patients each have a different view of the server via web-based dashboards. Server dashboards for patients show a simplified view of the data as compared to the physician versions.

In the athletic version of the system, the cloud server is not used. Analysis of insole data is performed on the smartphone and dashboards display the data immediately to the user. In addition, the athletic version optionally allows snapshot images of the dashboards to be automatically forwarded once per day to selected recipients via email – a desired feature for athletes who want to share performance with their coach.

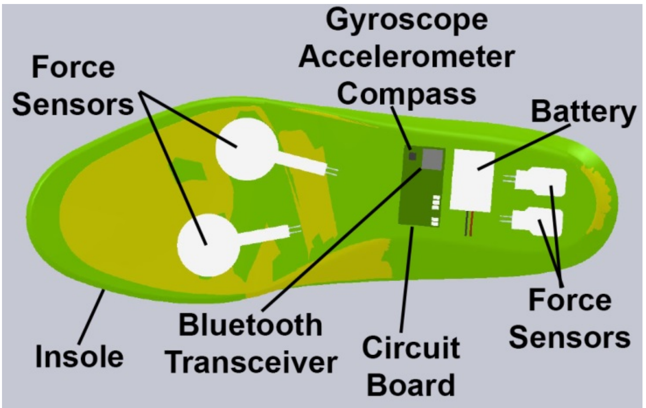

Figure 3. Major components contained inside the insole.

4. INSOLE HARDWARE

The major components of the insole are shown in Figure 3. In contrast to this current design, Deaton Engineering's initial design specifications for the insole in 2010 included the following:

- Four force sensors integrated into each of the two rigid insoles.
- Two accelerometers integrated into each of the two rigid insoles.
- A transmitter cabled to the insole used to collect and transmit data to the data collector (this transmitter was actually foreseen to attach to the leg, just above the ankle).
- A custom data collector, worn on the user's belt, that received data from the transmitter, provided interface to the user, and streamed data to a client personal computer.
- A personal computer that would send the data to the cloud based server for final processing.

During development of the insole hardware three major changes occurred:

- The realization that government regulators were beginning to approve medical devices that utilized smartphone technology moved the data collector from a custom device to the smartphone platform.
- Through testing, it became apparent that the user was not comfortable with the transmitter strapped to the ankle and would prefer a device that did not rely on this component. This led to integrating the battery, Bluetooth circuit and battery charger directly into the insole.
- The expansion of the capabilities of the insole that came to light during the Beta phase, including running gait and biking analysis, led to the development of a cast, semi-rigid, polyurethane insole to replace the rigid insoles used in previous prototypes.

Some of the major challenges during development included working with off-shore developers who had designed the software development kit (SDK) for the selected microprocessor. In the end, a U.S.-based developer was chosen to provide an alternate SDK. Another challenge was designing around a 9-axis motion sensor that had not yet been released to production. Adding this component greatly improved the design over the two accelerometers but added risk due to the selection of pre-production components. Increasing the data transmission rate between the insoles and smartphone was still another challenge as was sourcing the miniaturized electronics necessary to fit into the semi-rigid insoles.

5. SERVER AND DASHBOARDS

The StepRite® server runs on the CentOS operating system and is written in PHP, C++, and HTML5. Communication between the server and the smartphone applications is achieved by using a web service. The server, used only in the medical version of the system, performs several important tasks. First, the server is the only interface seen by the physician or physical therapist who prescribes a regimen of exercises for the patient and then monitors the results via the server dashboards. The server also contains the algorithms necessary to translate raw insole data into information for display. In addition, the server manages a database of patient information and collected data. An example physician dashboard is shown in Figure 4.

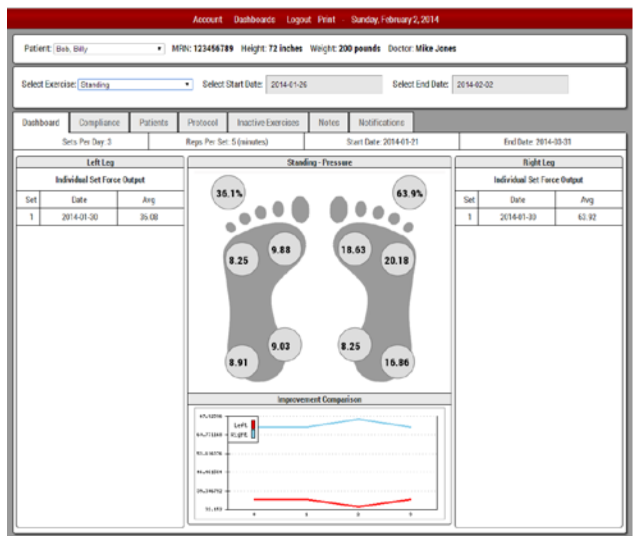

Figure 4. Physician dashboard for force analysis.

6. MOBILE APPLICATIONS

Creating the smartphone applications to interface to the insoles posed several challenges. In terms of the user interface there were no similar applications from which to compare. The StepRite® system was novel. The design began by soliciting ideas from physicians and trainers who created sketches, some of which served as the basis for the eventual screen designs. Feedback from beta testers proved very useful in tuning the designs. The athletic version and the medical version applications have a greatly different focus from the user point of view. Since the athletic version was not connected to the server, all data analysis and display would be performed on the smartphone. It was assumed that users of this version of the system would be much more technology savvy so great detail was put into the design of the application and screens. In contrast, the medical version was

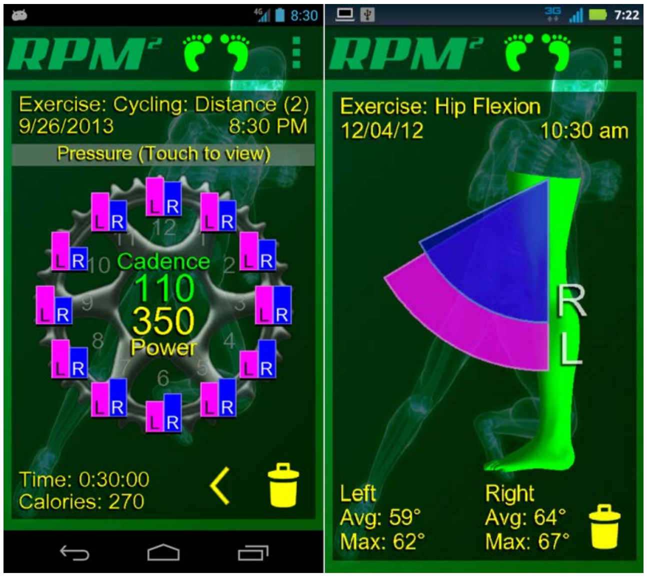

Figure 5. Athletic version smartphone application showing cycling dashboard (left) and range of motion exercise dashboard (right).

designed to be as simple as possible and provide both audible and onscreen prompts to the user when performing exercises. Examples screens from the athletic application are shown in Figure 5 while screens from the medical version are shown in Figure 6.

Another challenge during development was the data sharing feature in the athletic version. The goal was to share data by automatically emailing screenshots of app dashboards to the coach. In some cases the sheer number of dashboards available to the user became too much to fit into a few images that could be emailed efficiently. As a result, a separate set of email-version dashboards were created with the information in a condensed format.

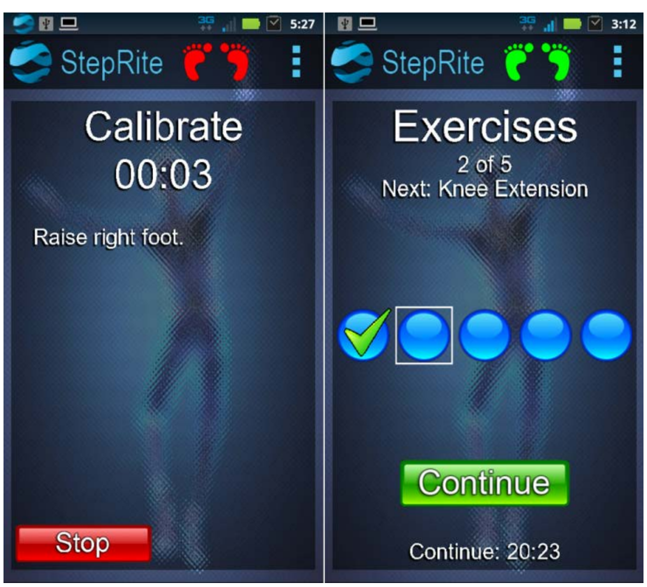

Figure 6. Medical version smartphone application showing exercise in progress (left) and regimen screen (right).

Another important task of the mobile application is to alert the user to any potential problems with the insoles. Small footprint indicators were placed at the top of the application screen and color coded to indicate the insoles status as shown in Table 1.

Table 1. Insole Status Icons

Color	Meaning
Green	Ready
Red	In use
Black	Not connected
Grey	Connected with errors
Blinking	Low battery

7. ALGORITHM DEVELOPMENT

One of the most creative aspects of the system development was the custom algorithms that were engineered. Algorithm development for the system generally falls into two areas – range of motion and gait. Range of motion includes exercises such as knee extension and toe raise while gait includes walking and running.

7.1 Range of Motion

For many of the exercises, it is important to use the noisy accelerometer data to detect and analyze the repetitions performed by the patient. This task is typical of unsupervised classification in machine learning - easy for a human to do, at least approximately, but relatively difficult to automate. Our overall approach was to:

1. Use the given accelerometer data to calculate an angle measure at each time slice.
2. Smooth the data by calculating weighted local averages.
3. Classify each angle data point as being part of a repetition or baseline (not part of a repetition).
4. Count the number of fully completed repetitions, and
5. Calculate the average angle inside each repetition.

The trickiest is step 3, the classification itself. Our first attempt was to use one threshold angle, classifying angles greater than it as being inside a repetition. But choosing an appropriate threshold is not as straightforward as it would seem. For example, choosing the average or median angle works poorly on data that contain long stretches of time outside repetitions. To make repetition detection more robust, we:

1. Sorted the angle data from smallest (least like a repetition) to largest (most like a repetition).
2. Considered one by one each threshold that separates a pair of adjacent angles.
3. Used that threshold to classify all angle data points in two clusters: baseline and repetition.
4. Calculated the sum of squared errors between data points and cluster mean for each of the two clusters, and
5. Chose the threshold that minimizes that within-cluster sum of squares (WCSS).

This approach, k-means clustering [3], is NP-hard in general but easy for one-dimensional data [5]. With fine-tuning here, such as weighting WCSS more for a baseline cluster than for a repetition cluster, we were able to mimic human repetition detection quite robustly given real data for a wide range of exercises. There is plenty of room for fine-tuning at each step to accommodate future exercises.

An example of range of motion data analysis using our method is shown in Figure 7. Our approach correctly identifies the six substantial repetitions, ignoring the noise around time 400 because it lacks sufficient duration and range of motion.

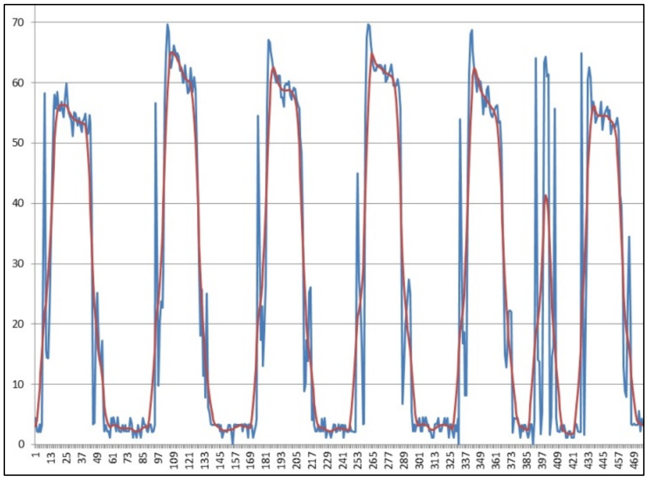

Figure 7. Jagged blue lines are raw data while smooth red lines are the data after smoothing.

7.2 Gait

TMAC was engaged by MedHab® to develop software for gait performance analysis with the goal of complementing the already existing range of static and quasi-static diagnostic measurements in its products. The so-called "gait algorithm" is based on numerical analysis of combined inertial and force sensor data collected at sampling rates in the 50 Hz to 100 Hz range. The code is implemented as a stand-alone software module that takes raw sensor data uploaded by the mobile phone app as the input, and produces averaged gait parameters as the output. The code was implemented using common C libraries and plaintext file I/O for ready compilation by a variety of OS platforms and integration into MedHab's IT infrastructure, leaving aggregation of the data over multiple exercises to be performed at the app level.

Gait algorithms must make sense out of highly dynamic events buried in noise and sensor artifacts; the code must discern patterns which themselves vary heavily across different user anatomies, gait styles, and terrains. Among the various algorithm outputs, certain ones such as the estimation of stride distance or gait phase detection based on inertial measurements alone are well-recognized problems which have been attempted by several researchers at different degrees of sophistication [1,4,6]. For distance computations in particular, there are two broad techniques - one by double integration of the forward acceleration components, and another by statistical correlation of the acceleration signals drawn from a large number of test cases of known stride distance. A complete description of each of these is outside the scope of this manuscript, and although TMAC's gait algorithm includes stride distance estimation by the former technique, some of the arguably more valuable and precise measurements - in particular those relating to bilateral performance - are reported based on event timing. These are discussed below, as we break down the algorithm process into its four constitutive phases of pre-processing, discretization and time-based analysis, stride distance estimation, and output reporting.

7.2.1 Pre-processing

We found that a short preamble to each exercise, where the user stands evenly on both feet and then raises each foot in turn, was effective in increasing the quality and reliability of the computations by providing reference sensor values. During the preamble the system records gyroscopic sensor offsets, obtains suitable, subject-specific threshold values for foot forces, and performs a diagnostic health check on the sensors. Computationally, the algorithm first applies the gyroscope offset to correct for static sensor bias, and uses the acceleration offset to compute an "absolute total velocity" channel which is used in later processing. Importantly, the algorithm performs an epoch time adjustment to synchronize or align in time the left and right foot data, which is essential for step-wise (foot-to-foot) calculations since each channel runs on its own microprocessor and time base. This procedure is predicated on an accurate epoch time timestamp being written into each microprocessor during exercise initialization, and is otherwise insensitive to wireless data transmission latencies.

7.2.2 Discretization and time-based analysis

Regardless of the measurements reported, an essential task in gait analysis is discretization, or time-based identification of individual stride events. This is done based on a search algorithm that finds "zero-total-acceleration" events in the data stream for each foot. These events represent ground contact of a given foot with the floor, where motion is momentarily suspended while the subject stands still or his/her other foot swings. Comparing the ground strikes of one foot with respect to the other along an equalized or common time base (thus the epoch synchronization) allows for calculation of step time; then, for any given foot, ground contact time allows determination of the average cadence (strides per minute, from time in between ground contacts) as well as average swing time (expressed as a ratio of total stride time) and force readings (reported as a percent of the standing value determined during initialization). The program outputs the overall number of strides as a reference value, reported by multiplication of the average cadence and the exercise clock time.

7.2.3 Stride distance estimation

Following the time-based calculations, the algorithm proceeds with the estimation of stride distance. This is done by the technique of double integration of the forward acceleration components in the sagittal plane. The foot angle required for this calculation is found from single integration of the gyroscope signal normal to said sagittal plane, with the initial angle condition estimated from accelerometer signals at ground contact under quasi-static total acceleration conditions. This is accompanied by several filtering and data conditioning steps prior to and after integration whose detail is omitted herein. These calculations represent an estimate of distance, and degrade as the speed of the events increase from slow walking to fast running.

Figure 8. Measuring/surveyor wheel.

7.2.4 Output reporting

Prior to final data reporting, and throughout the various categories of computations, the algorithm filters out sporadic or errant data from individual strides amongst the totality of the strides recorded. These events are difficult to predict, and occur due to signal noise, mechanical noise from natural terrain and gait variations, and other artifacts which occasionally foil the rules built into the algorithm; we therefore find that statistical reporting of the data, versus reporting values for each individual stride, is both more understandable and reliable. This data filtering is performed at several levels, first by gross threshold checking (e.g., events that are known to be too short or too long), and then by more targeted outlier detection techniques such as the Modified Z Score and interquartile averaging. Final values are output by the code based on said statistical averages and under the assumption of a repeating pattern. The final output data set includes clock time, average cadence time in strides per minute, number of strides, average swing time for each foot, average left-to-right and right-to-left step time, average foot force, and estimated average stride distance.

Testing of the algorithm output has been performed for cadence time and estimated stride distance. Swing vs. total time and step-wise calculations require equipment capable of analyzing motion with millisecond accuracy, which entails the use of highly sophisticated, externally instrumented tracks. For the former, TMAC has used a flat, straight test track 200-220 feet in length with start/end markings, measured with a measuring or surveyor wheel within ½ foot accuracy. The measuring wheel is shown in Figure 8.

TMAC uses a test track of 212.5' (or 2,250"). Insofar as distance calculations are regarded as estimates, we do not report specific accuracy values, but results are in general agreement with published references which can be as low as single-digit percent error depending upon the dynamic content of the data. The test track outside the TMAC laboratory is shown in Figure 9.

8. CONCLUSION

The development of the StepRite® system involved the input of numerous individuals and organizations. Surveys were conducted among members of the medical community, including orthopedic surgeons and physical therapists in order to understand the need that existed in terms of enhancing the rehabilitative process. The input obtained helped the makers of the StepRite® system to understand the limitations and challenges faced by members of the rehabilitation community as it exists today. The input provided by members of the medical community as well as an Advisory Board steered the identification of exercises most commonly employed in rehabilitation protocols and which were subsequently added as exercises to the protocol generation feature of the web-based server. The type of data that is collected and the manner in which data is presented represents another area in which the input of healthcare providers was solicited. On the athletic side, executives of MedHab® continue to solicit and receive feedback from the sports community with the result that the athletic version, introduced into the commercial market in late 2013, is also still evolving. The system presented is novel. At the time it was invented and during the early product development there were no competing products.

Figure 9. Test track outside TMAC laboratory.

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