AGIS: Automated Tool Detection & Hand-Arm Vibration Estimation using an unmodified Smartwatch

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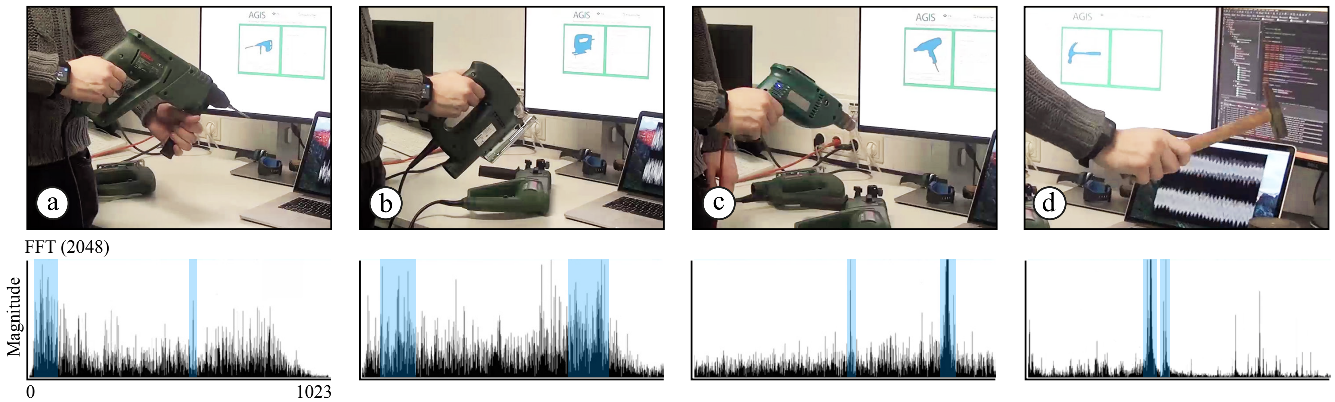

Figure 1. *AGIS* is a smartwatch-based system, which is capable to learn and recognize tools based on their emitted sounds, characteristic motions, and vibration patterns. In this example, we can already see unique differences in the FFT spectrum of the emitted sound wave from a a) Hammer Drill, b) Jigsaw, c) Drilling Machine, and a manual d) Hammer. Based on this data, *AGIS* is capable in estimating a daily HAV exposure dose, which hasn't been demonstrated for a wearable system yet.

ABSTRACT
Over the past three decades, it has been known that long-lasting and intense hand-arm vibrations (HAV) can cause serious diseases, such as the Raynaud- / White Finger-Syndrome. In order to protect workers nowadays, the long-term use of tools such as a drill, grinder, rotary hammer etc. underlie strict legal regulations. However, users rarely comply with these regulations because it is quite hard to manually estimate vibration intensity throughout the day. Therefore, we propose a wearable system that automatically counts the daily HAV exposure doses due to the fact that we are able to determine the currently used tool. With the implementation of *AGIS,* we demonstrate the technical feasibility of using the integrated microphone and accelerometer from a commercial smartwatch. In contrast to prior works, our approach does not require a technical modification of the smartwatch nor an instrumentation of the environment or the tool. A pilot study shows our proof-of-concept to be applicable in real workshop environments.

ACM Classification Keywords
H.5.2: [User interfaces] – Input devices and strategies.

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INTRODUCTION
Most tools used by handcrafters or heavy workers emit considerable vibrations that spread throughout the whole body. Due to the long-lasting and intense vibration of hand and arm, irreparable damage can be caused to our sensorineural [1], and our muscular [2] system. These diseases are referred to as HAV- / Raynaud- / White Finger-Syndrome. Nowadays, there are regulations to protect workers, which demand to evaluate vibration exposure and to assess potential risks. For example: The German Vibration Occupational Safety and Health Regulation [9], which is similar to the European regulations [4], obliges the employer to abide with the limit of the daily dosage of A(8) = 5 m/s² and to establish a vibration reduction program when exceeding a daily dose of A(8) = 2.5 m/s². Tools that are currently used to assess HAV exposure durations and intensity are expensive, disturb the workflow or may be applied only sporadically or rarely due to the high costs. In contrast to a manual evaluation and proposed solutions in research [10,12], we set the goal to explore a more natural and unobtrusive way of logging, while not relying on fragile custom hardware prototypes. Therefore, we utilize a commercial and robust smartwatch, which incorporates a great variety of integrated sensors.

We call our developed system: *AGIS*: *Automated G-force vibration Interpretation on Smartwatches*, which contributes an unobtrusive wearable system that enables a:

- Determination of the current tool being used based on the data of the integrated microphone and accelerometer,
- Estimation of the HAV exposure doses in respect to the legal regulations.

RELATED WORK

The most recent report of the Institute for Occupational Safety and Health of the German Social Accident Insurance [8] has shown that many workers who are exposed to significant HAV do not keep track of vibration exposure or just apply simple methods, such as using a stop watch. However, the actual exposure time is not being measured, but estimated based on the mean production time and personal experiences. Such subjective estimation is inaccurate, since the guessed time of use is often much lower than the actual HAV exposure doses [8].

In other research, we can find several solutions to overcome the problem of tracking the tool being used, such as by using radio transmitters. RFID tags are being attached to the tools and read out by a wrist-worn RFID reader [5]. In this setup, we can identify the tool and calculate the duration it is held. However, we do not know whether the tool is indeed switched on. Therefore, the duration of exposure can only be roughly estimated. Similar recognition systems with other technologies include NFC [7], WiFi [13], or Bluetooth [3], all of which yield the same drawbacks.

Moreover, distinguishing tools based on their execution style has been proposed in 2004 by Lukowicz et al. [11] and in 2006 by Ward et al. [12]. While they attach a loose microphone and an accelerometer to the user's arm, almost ten different tools have been demonstrated to be detectable with an accuracy of >90% based on a user-dependent classification. Although such types of sensors look promising for a tool detection, they remain bulky prototypes which are not applicable in a real shop floor.

A very recent project, EM-Sense [10], represents a more advanced approach that utilizes an Electromagnetic Field Sensing in order to demonstrate the recognition of a unique signature that is created when the device is worn and actually switched on. This way, a tool identification and the exact duration of use can be determined. On the other hand, we require a customized smartwatch, which is bulky and prone to break. None of these afore mentioned projects are applicable in real scenarios, as none of them demonstrated an implicit way of determining vibration exposure doses, which is however the aim of *AGIS*.

IMPLEMENTATION

We implemented the *AGIS* system on a SimValley AW 429RX, which is an autarkic Android 4.2 smartwatch and thus fully independent, since it is not being required to rely on a smartphone such as Android Wear Devices. We utilized the integrated microphone, which provides 8kHz with 90.31db, and the integrated Bosch BMC050 12bit accelerometer. On the watch, we process and visualize the data. In addition, important information, such as a tool change, is being synchronized with a web server via the HSPA internet connection as well. The watch-face provides a visual representation – a circle graph – of the calculated HAV doses in respect to the daily limit (5.0m/s^2) imposed by legal regulations [9].

Figure 2. The *AGIS* Android app running on an autarkic smartwatch (SimValley AW 429 RX).

Sensor Quality

A precise determination of HAV requires high quality sensors, since some tools emit high amplitude- and high frequency- vibrations. Ascertaining the correct magnitude requires applying a high g-force sensor, which is capable of providing sampling rates up to 1000Hz. Unfortunately, these professional sensor solutions are expensive, bulky, barely mobile, and not comfortable to use.

In contrast, accelerometers or gyroscopes implemented in smartwatches show a lower quality. Usually only g-forces up to 8g and low sample rates such as 50Hz are being supported, such as in our case for the SimValley AW 429 RX. Following the Nyquist-Shannon-Theorem, we can therefore only recognize vibrations up to 25Hz, which is insufficient for tools such as a grinder that is running at 150rpm. These constrains disable us to provide an accurate calculation of actual HAV intensity.

HAV Exposure doses

To deal with the poor sensor quality, we developed a methodology that circumvents the hardware limitations and thus still enables us to determine the daily HAV exposure doses. Our solution relies on a calculation based on the HAV intensity ratio reported in the datasheet for each tool. Therefore, we now only need to correctly identify the tool that is being used and to create a database containing all tool specific HAV intensity ratios.

(i) Once the tool is known to the system, we can easily calculate the daily doses based on the HAV intensity ratio from the datasheet (a_{hv} in m/s^2), the duration the worker is exposed to the vibration (T_{exp} in hours), and the daily limit of working hours (T_0 in hours).

$$A(8) = a_{hv} \sqrt{\frac{T_{exp}}{T_0}}$$

A(8) describes the daily HAV exposure doses, which is consequently also specified in m/s^2.

(ii) When using multiple tools during the day, we have to sum the HAV exposure periods $A_n(8)$ in this manner:

$$A(8) = \sqrt{A_1(8)^2 + A_2(8)^2 + A_3(8)^2 + A_4(8)^2 + \ldots}$$

(iii) Given a situation in which a tool cannot be detected or the datasheet is unknown to the system, *AGIS* will estimate the HAV intensity ratio (a_{hv}) based on the maximum amplitude of each axis as follows:

$$a_{hv} = \sqrt{a_{hvx}^2 + a_{hvy}^2 + a_{hvz}^2}$$

Note: In order to only receive the vibration intensity, we apply a high-pass filter to remove all arm/hand motions.

Tool detection

Similar to previous research [12], we are also utilizing sound (Microphone), and vibration and movement sequences (Accelerometer) for a tool detection.

As a first step, we only query the integrated smartwatch microphone with 8kHz, which enables to sense sounds up to a range of 4kHz. After creating a *Fast Fourier Transformation (FFT)* on the unfiltered audio signal, we can already see substantial differences which allow to identify the tool being used based on the predominant frequencies. With this sole feature, we could demonstrate a flawless detection (of >90% in a lab study with 3 participants and 10 trails for each tool) of 4 different tools, which are: a) Hammer Drill, b) Jigsaw, c) Drilling Machine, and a manual d) Hammer – *see Figure 1*.

Also in accordance with literature, distinguishing tools which emit similar sounds and which show no diversity in physical execution style, remains to be difficult. For a possible solution, we require to further enrich our data set with accelerometer data in order to determine unique vibration patterns. With this new setup, we compute 71 features (most commonly known in literature) on both the audio and the acceleration data. We have chosen a robust and energy-efficient classifier, a *J48 decision tree*, which then ranks and selects the most meaningful attributes, which are usually about 9-15. Even though plenty of features correlate, the most meaningful ones include: *Mean, squared Mean, Mean Crossings, Root Mean Square, Median, Variance, Standard Deviation, Dominant Emphasis Frequency, Max. Amplitude Frequency, Signal Energy, Zero Crossings, Activity Units...*

With this approach, we are now enabled to also train several other activities to the *AGIS* system (*see web interface in Figure 3*). It has been shown that an increased set of learned activities and tools decrease overall accuracy of the system.

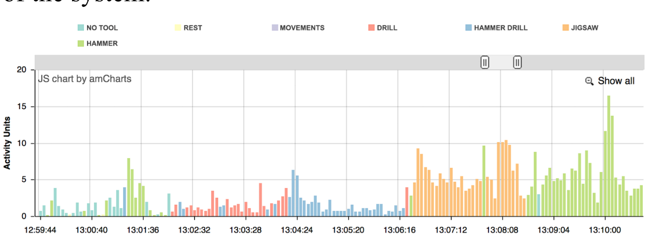

Figure 3. An online platform allows to display the performed activities and tools being used.

IN SITU PILOT STUDY

We evaluated the practicality of our solution through a detailed *in situ pilot study*. Our goal was to observe an actual worker using our system and to learn more about what it is like to use it in a real shop floor. Aside from that, we collected data to further evaluate the recognition rates.

Study Setup

In a metal workshop, we equipped a worker with three *apparatuses*, which were the smartwatch running *AGIS*, a GoPro Camera, and an external noise sensor system to gather ground truth data. Before running the actual test, the user had to conduct a 2-5 minute training phase, in which the system learned four similar grinding tools (*see Figure 4*). In addition, a resting / "no grinding"-phase has been trained, which was however impure since the worker was doing random other things such as running around in a very noisy shop floor. The worker was not instructed to perform a specific *task*, but instead to just continue his usual daily work, which basically included grinding metal parts.

Figure 4. In our *pilot study,* the worker trained four similar grinders, which were: a) angle grinder Hilti, b) angle grinder Milwaukee, c) pneumatic grinder, d) wobble disc grinder. The *AGIS* smartwatch system was then distinguishing those and estimating the daily HAV doses.

Results

During the period usage, which was about an hour, our system created 2784 instances using a non-overlapping window approach (1.28 seconds per window).

As we can also notice in *Table 1*, the wobble disc grinder has not been used. However, the *AGIS* smartwatch system sometimes misclassified other grinders (especially the pneumatic grinder) to be the wobble disc grinder (with a confidence of 34%). That is why the pneumatic grinder only scores 42.2% instead of 75% TP. The generally quite low accuracy is due to several factors, such as:

- The grinders have been used with various other grinding discs, which were not learned by the system beforehand
- Emitted random noise from other tools from neighbor works turned some audio features ambiguous.

According to the observation by the video/sound analysis, the *AGIS* smartwatch system overestimated the HAV exposure by A(8) = 0.2m/s^2, which is around 11%.

Runtime (*Smartwatch*) [m/s^2]	**Runtime** (*Video/Sound*) [m/s^2]	**Error** [m/s^2]	**Accuracy** (*True-Positive*) [%]	**HAV Exposure A(8)** (*Smartwatch*) [m/s^2]	**HAV Exposure A(8)** (*Video/Sound*) [m/s^2]	
17:10	14:38	2:32	**79.6**	2.9	2.47	**a**) angle grinder Hilti
08:25	05:25	03:00	**83.5**	1.12	0.72	**b**) angle grinder Milwaukee
08:09	13:03	-04.54	**42.2**	0.17	0.28	**c**) pneumatic grinder
03:04	00:00	03:04	-	0.08	0	**d**) wobble disc grinder
22:34	26:17	-03:43	**82.1**	0	0	no grinding
Total HAV Exposure A(8)				**2.1**	**1.9**	

Table 1. Comparing *AGIS* to the ground truth in terms of HAV Exposure doses and Tool Identification

Based on our observations and on the worker's comments (»*…executed my tasks in a usual speed* […] *at some point, I even forgot that I was being tracked.*«), we can state that the *AGIS* smartwatch system did not hinder the worker performing his daily work tasks in any way. This important factor is often not considered in other research projects.

»*... most time of the day* […] *I'm using grinders, but I never track the time* [*of usage*]. […] *make up a number at the end of the day, I can write in the sheet before leaving.*« In contrast, *AGIS* never requires the worker for any administration. Instead, *AGIS* automatically tracks the time of the tool in use and calculates the daily HAV dose. Still, additional tweaking and a broader training phase would further improve the quite high deviation of 11%.

What we can also learn from this in situ study is, that in a real shop floor environment unanticipated events, such as background noise, unforeseen movements, etc., always occur (during both: training and testing phase). This apparently had a huge negative impact on our accuracy rates. Previous researchers were able to report much higher rates, because (1) they did not deal with these issues in laboratory conditions and (2) they usually only focused on distinguishing very dissimilar tools. In contrast, our study is carried out in a real shop floor, while we were trying to distinguish between four similar tools (grinders) that somehow yield same executions styles, similar vibration patterns, and similar sound emissions. Still, if not considering the pneumatic grinder, we already achieve an overall accuracy rate of 85%, which would be sufficient in practice, since their HAV ratios are actually quite similar.

CONCLUSION

In this research, we investigated the technical feasibility of a smartwatch system to determine an estimation of daily HAV exposure doses by the means of a tool detection that is based on the emitted vibration and sound. Even though we could implement a mobile smartwatch system, we still see this project as a proof-of-concept. Applying *AGIS* in a usual workday would still require broader user tests and additional tweaking to reliably distinguish similar tools. In future, we envision smartwatches to play a critical role for a workshop-based monitoring, which potentially supports the reduction of stress and administrative pressure on workers.

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