Classification of Human Interactions with Tools Using a Tool-Mounted Wireless Sensor Node to Support Sustainable Manufacturing

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***Abstract*—In this contribution, a customized wireless sensor node with onboard acceleration sensor is applied to support optical motion analysis systems. An integrated signal processing algorithm to classify interactions between user and tool is developed for the specific use case of a cordless screwdriver. Results of the first demonstrator evaluation are discussed with respect to further development of the sensor architecture for smart tools.**

Keywords-Human-centered automation; smart tools; wireless sensors; sustainable manufacturing

I. INTRODUCTION

Despite many efforts to automatize manufacturing processes, the human worker is still an essential element in the production line. Humans possess unique skills which recently no robot or machine tool can imitate. Especially when it comes to flexible production, such as in mass customization, employing machines becomes extremely costly due to the need to frequently reconfigure the equipment. On the other hand, qualification and education are essential in order to have flexible workers. Especially industrialized countries with an ageing workforce fear the loss of know-how due to the expected retirements of many experienced workers in the next years. This leaves a lack of staff able to teach the inexperienced beginner. Instead of compensating this loss with simple technological substitution, systems of human centered automation solve the problem by automatically supporting workers in their tasks. These systems enhance the workers' skills, e.g., by amplifying the force or intuitively teach them.

As a core component of these aids, an intelligent sensor system is introduced which is able to provide sufficient information to recognize the actions of the human in order to react appropriately, e.g., by activating actuators or notifying the user. Optical systems suit most of these tasks due to their non-invasive operation principle making bulky equipment to wear obsolete. However, when interacting with objects, e.g., tools, the detection becomes hard due to high variance in appearance and occluded view. Hence, it is proposed to add an additional three-axial acceleration sensor directly at the objects to support the optical systems.

As a dedicated use case for the setup, a teaching system is chosen, which interactively provides the user with information about the currently conducted assembly task. The sensor information provided here is used to identify the current work step, sequence and proper execution in order to provide the user with feedback. On the basis of the results achieved with the prototypical setup, further developments of wireless sensors are discussed with respect to the defined use-case.

II. RELATED WORK

Past work has focused on gesture recognition or object interactions involving the use of either a complex system of acceleration sensors in combination with RFID sensors [1][2], a microphone [3][4], a gyroscope and a magnetic field [5] or a force sensor [6]. Multi-sensor approaches have been shown to improve recognition performance [7], however, they require more equipment.

Normally accelerometers have been attached to a part of the body or the object whose movement is considered as characteristic for the activity performed [8]. Only the authors in [9] have a tool mounted accelerometer. More commonly used was a wrist worn sensor [1][3][4]. However, a significant disadvantage of attaching the sensors to the body is that, depending on their size and weight, they can noticeably limit the freedom of movement.

As diverse as these sensor combinations, a variety of algorithms have been implemented to detect movement patterns. A variety of approaches to obtain characteristics of the acceleration data for classification have been employed. One option to extract features from the acceleration signal involves their direct derivation from the time domain of the signal. This includes common statistic techniques, such as simple integration methods, mean, standard deviation, skewness, kurtosis, and eccentricity. Furthermore, some researchers have analyzed the signal's frequency spectrum to identify the dominant frequencies. A more recent approach is the wavelet analysis [8]. Here, the original signal is decomposed into a series of coefficients, which contain spectral and temporal information about the original signal. Based on these coefficients, temporal instances with a change in the frequency response of the original signal can be identified [10]. Several researchers have shown that the extraction of features from the time domain of the signal allowed classification performances partly >90% [8][11]. Moreover, since for low sampling frequencies, the detection of time dominant features is superior to the detection of

 ISBN: 978-1-61208-425-1

frequency dominant features [12], we follow a time domain approach.

For the most human activities, hand movements are significant. Yet recognizing the relevant ones in a continuous data stream is difficult. One reason is the hand's high degree of freedom: the same gesture can be performed in different ways. In addition, hands are the most active parts of the body, being constantly in motion even without containing relevant information [3].

Since optical sensors have their problems with classifying fast movements [7] and since they are susceptible to obstruction [4], realizing such a recognition component only with vision based methods is difficult. Especially in a workshop, the distinction between man and tool for the detection of human interactions with tools is problematic.

The implementation of micro system technology (MST) for the described tasks of sensing allows for innovative approaches with respect to the described application. The inclusion of sensor interface, data processing, radio frequency communication and autonomous power supply enables numerous tasks that can be added to the already existing functionalities. Moreover, the high miniaturization potential of MST solutions supports applications that require minimum system size and –weight for least interference with the subordinate technical system and already existing periphery. Small distributed systems are mainly applied for the process monitoring of production equipment [13], but also logistics support with electronic functions beyond RFID identification are a growing sector. Benefits on sustainability from employing an increased number of micro system technology in industrial environments such as manufacturing are currently addressed within the framework of the Collaborative Research Center (CRC) 1026, e.g., [14]. A broader look at the trade-off between benefits and impacts of the additional micro systems as well as the inclusion of teaching tools into sustainability assessment will be part of the ongoing research within CRC1026.

III. CONDUCTION OF THE STUDY

As physical instantiation of the demonstrator, a three-axial acceleration sensor with wireless communication capabilities was attached to a hand-held drilling machine (Fig.1).

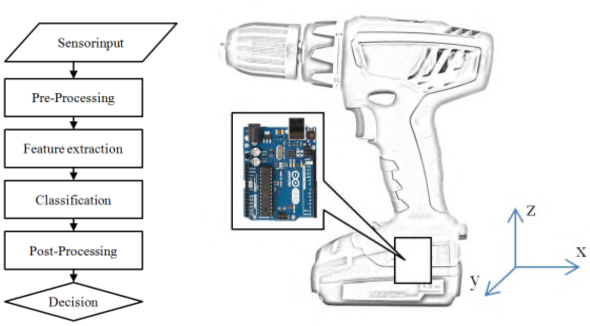


Figure 1. Sensor module attached to drilling machine (right). Pathway of processing the sensor-data till final decision (left).

Five typical drilling activities were examined:

- Picking up the drilling machine from a work table,
- putting down the drilling machine on a work table,
- successively rotating the drilling machine in the sagittal and frontal plane by 90°,
- switching on the drilling machine without contacting the work piece,
- and switching on the drilling machine with contacting the work piece.

In order to develop algorithms that allow the identification of movement/acceleration patterns, the referred activities were recorded five times with short interruptions between each measurement followed by five continuous measurements in a row.

IV. SENSOR HARDWARE AND DATA AQUISITION

The proposed first generation of a sensor node (Tab. II top) is based on open source hard- and software using Arduino UNO R3 board with ATmega328 microcontroller, a customized acceleration sensor layer (ADXL326) and integrated Bluetooth communication interface (BLUETOOTH-SHIELD V2.2). With this setup, wireless communication with a central personal computer is established to transmit all acceleration data required for the classification of human interactions. Through a micro-USB port the Arduino-microcontroller is programmed using customized firmware, covering all data assessment (temperature, 3-axes acceleration), ID of the node and the communication with the Bluetooth interface. Due to the universal functionality of soft- and hardware of the sensor, energy demand is still comparatively high with approx. 110mW in active mode when operating continuously. The applied hardware can therefore be considered as a demonstrator on primary stage for the evaluation of the described scenario of a MST equipped drilling machine. The measurement routine applied is described in the following sections.

V. PRE-PROCESSING

In this section, the pre-processing of the raw data stream is briefly explained. The raw sensor data which is mean adjusted and smoothed. Since the size of the sliding window affects the accuracy and delay of classification, it should be adapted to the characteristic duration of the activities of interest [4]. In order to identify the time intensive activities like picking up or putting down the drilling machine, as well as moments of rest properly, a sliding window with two window sizes of 0.6 s and 1.2 s and a minimal overlap of 1/fs is chosen. With the objective to limit the dynamic range of the acceleration signal to a comparable interval and to implement a state-independent classification, it is essential to align the basic level of acceleration for different machine states on a uniform level. This is realized by a mean adjustment with a signal's outcoming arithmetic mean of zero. The acceleration signal is affected by short frequency signal changes. In order to ensure a reliable detection of

 ISBN: 978-1-61208-425-1

individual activities, signal smoothing is indispensable. For this purpose, a moving average filter has been chosen as it allows efficient computation and quick responses to changes in the amplitude [13]. Despite its simplicity, the moving average filter is optimal for reducing random noise while retaining a sharp step response. On the downside, it allows inacceptable frequency separation [16]. The size of the window in the averaging process has been chosen according to the recommendations in [13]. For fast movements, the recommended time frame ranges from 25 ms to 50 ms, for slow movements, time frames from 100 ms to 200 ms are recommended. Since the activities considered in this work include both – fast and slow movement patterns, an empirical based time frame of 160 ms has been chosen.

VI. FEATURE EXTRACTION

While the selection of features is a critical task for a good recognition performance [4], this paper does not focus on the search for the best possible features. Rather, the goal is to develop an algorithm which leads to an acceptable recognition performance for the underlying problem using low computational effort. One of the main challenges of the pattern recognition task is to distinguish between relevant and non-relevant activities [4]. Characteristic features which allow such discrimination are essential for the classification task. Irrelevant data should be discarded at the same time [17][18]. To do so, the short window activity is quantified by the empirical activity measure (Act) described in [19]. The faster the movement, the greater the change in the acceleration signal is. Act uses these changes of the acceleration vector to detect the sensor's movement represented by a single indicator. While in a static state of approximately zero, the empirical activity of the sensor increases when the sensor is moved. By combining the acceleration of all sensor axes to create one single indicator, movements and non-movements can be distinguished, even if the acceleration changes along one axis. If Act does not meet an empirically determined threshold, the window is classified as non-relevant. Otherwise, the activity is considered relevant and will be examined more in detail.

The goal of implementing a minimum activity criterion is to separate relevant from random, non-relevant information of the acceleration signal. But separation turned out to be difficult, since many diverse movements of the drilling machine exceed the minimum activity threshold, although this information is non-relevant. A comparison of the empirical activity measures of high-frequency and low-frequency ranges of the acceleration signal turned out to be the solution to this problem. It utilizes the circumstance that human movements are characterized by low frequencies [8], fast machine movements by high frequencies. The separation of high and low frequency signal components is carried out by computing the deviation between the smoothed and the original signal.

A. *Picking up/ Putting down*

If, at the beginning of a machining sequence, the machine is in an upright position, the smoothed vertical component of the acceleration signal is checked for a characteristic pattern for picking the drilling machine up (Fig. 2). A simple template matching algorithm consisting of a successively scaled sine-function-section turned out to be sufficient for detecting the picking up. As comparison criteria, the maximum and the mean absolute deviation between the smoothed signal and the sine-function are used. For not having to apply the procedure to each data-point within the considered window, the moving standard deviation of the vertical signal component is examined for whether it exceeds a sequence of empirical thresholds. If the picking up of the drilling machine has already been recognized and if the machine is in an upright position, a template matching algorithm is carried out to recognize whether the drilling machine is put down. Except a customized template, this procedure corresponds to that of picking the drilling machine up.

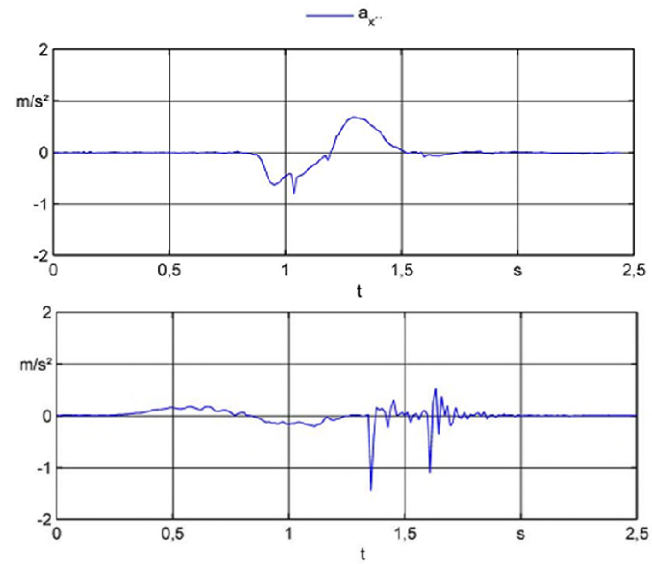


Figure 2. Example signals for activity ‘Picking up’ (top) and ‘Putting down’ (bottom).

B. *Rotating the drilling machine*

To determine whether the drilling machine was rotated in the sagittal or frontal plane, the mean acceleration along all sensor axes in a short time window were calculated and compared with their previous results. If there was an acceleration change of at least ± 0.5 g, activities in the current window were classified as rotating the drilling machine.

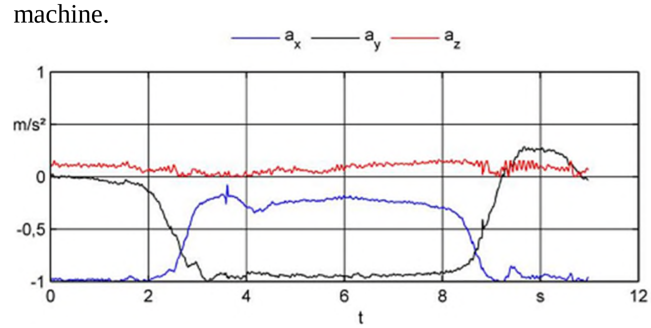


Figure 3. Example signal for activity ‘Rotate’.

C. Switching on the drilling machine

If the previously described activities have not been recognized, the signal is analyzed for patterns of drilling movements. The distinction between switching the drilling machine on with and without contact to the work piece is decided via the sensor's horizontal acceleration (Fig. 3). If the drilling machine is switched on with contact to the work piece, low-frequency resonances at high amplitudes along the horizontal axis are observed. This discrepancy is quantified by the empirical activity measure, isolated applied on the horizontal axis.

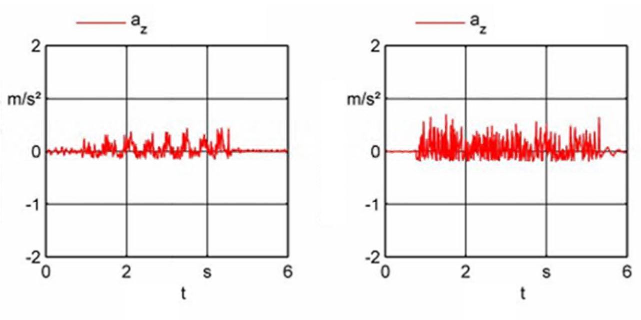


Figure 4. Example signals for activity ‘Switch on without contact’ (left) and ‘Switch on with contact’ (right).

VII. CLASSIFICATION AND POST PROCESSING

Although there are a number of classifiers for pattern recognition, to make the classification as understandable and as easily extendable as possible, a simple decision tree has been chosen for classification. A simple decision tree allows a classification of user activities in real time [20] and provides, in terms of movement detection, a good compromise between accuracy and computation time [21][1].

In the first step, the current window of the acceleration signal is analyzed for patterns indicating ‘rotation of the drilling machine’. This action can potentially generate an empirical activity higher or less the minimum empirical activity. If this is not the case, there is no relevant information in the observed window. If it exceeds, the drilling machine's position in relation to the vertical axis is identified. If the drilling machine has not yet been picked up from the worktable, the current window is analyzed for typical acceleration patterns for picking up the drilling machine.

In the next step, if the direction of gravitational force is in alignment with the vertical axis and if the drilling machine is already picked up from the working table, the current window is analyzed for patterns of putting the machine down. With sufficient match, the section is assigned accordingly. If there is no match, a comparison of the empirical activity measures of the high- and low-frequency ranges of the acceleration signal is carried out to determine whether there was movement in the window or the drilling machine has been switched on. In a predominance of the high-frequency activity, there is, depending on the empirical activity of the horizontal axis, a switched on drilling machine with or without contacting the work piece in the observed window.

A subsequent post-processing of the classification results on the basis of empiricism and context knowledge has been indispensable. For this purpose, the classification results of a series of multiple windows are linked adequately to a unitary class.

A. False positive detection of putting down

The false positive detection of putting down the drilling machine is based on the assumption that it indicates the end of a machining process. After that there should be no action until the machine is picked up again. If a signal section has been wrongly assigned to ‘putting down’, and within a certain time period another empirical minimum activity threshold exceeding acceleration has taken place, the false-positive detection corrects the wrong ‘putting down’ classification result to ‘movement’. The threshold is based on the obtained training data and has been determined by the empirical activity that delimits the hand held from the down put drilling machine. The reason for the wrong assignment is the similarity of the acceleration pattern of ‘movement’ and ‘putting down’.

B. False negative detection of putting down

Depending on the user and surface, there is a large variety of corresponding acceleration patterns for ‘putting down’ movement of the tool. Since a correct assignment of these patterns is difficult with the developed algorithm, it is necessary to correct the classification result in case the ‘putting down’ of the drilling machine has not been recognized. Similarly to the false positive detection, the false negative detection is based on the assumption that ‘putting down’ indicates the end of a machining process, with no subsequent changes in the acceleration signal. Hence, if ‘putting down’ has not been detected, and if the empirical activity is not exceeding the threshold mentioned before for several time windows, the prior detected activity must have been ‘putting down’.

C. Minimum length for drilling

To avoid a false recognition of ‘rotating the drilling machine’ instead of ‘drilling’, an empirical based minimum duration for drilling is used.

D. Putting down priority and majority rule

Due to the similarity of the characteristics occurring during ‘putting down’ with those of moving or switching the drilling machine on, short sequences of nearby windows occur in which an assigned ‘putting down’ is confused with another activity. In such cases, the putting down priority assigns ‘putting down’ to the entire window sequence. In sequences of nearby windows with different assignments to ‘movement’ or ‘switching’ the drilling machine with or without work piece contact, the majority rule assigns the entire sequence to the activity most frequently encountered in the sequence.

VIII. EVALUATION

The performance of the classification algorithm has been evaluated by determining classification accuracy (percentage of correctly classified test data). Test data from three male and one female operator have been analyzed. Three operators are right-handed. One is left-handed. Each canditate performed a predetermined sequence of following activities:

- picking up the drilling machine from a work table,
- four times of switching the drilling machine on without contacting the workpiece, each in a varied state,
- four times of switching the drilling machine on with contacting the workpiece, each in a varied state,
- putting down the drilling machine on a work table.

Tab. I shows the recognition results in an aggregated confusion matrix. For a sampling frequency of 82 Hz with an overall performance of 96 %, 100 % recognition accuracy has been achieved for ‘picking up’, ‘putting down’ and ‘rotating’. Since all these activities have similar characteristics, the only confusion was at distinguishing ‘switching the drilling machine on’ and ‘with or without contact to the work piece’. However, accuracies of 89% and 91% respectively could still be achieved.

TABLE I. RECONGNITION ACCURACY OF THE IMPLEMENTED ALGORITHM FOR SELECTED MOVEMENTS

Picking up	Rotating	Switching on (no contact)	Switching on (contact)	Putting down	Movement	Total	Class	Accuracy (%)
40	0	0	0	0	0	40	Picking up	100,00
0	400	0	0	0	0	400	Rotating	100,00
0	0	145	7	1	7	160	Switching on (no contact)	90,63
0	0	13	143	0	4	160	Switching on (contact)	89,38
0	0	0	0	40	0	40	Putting down	100,00
40	400	158	150	41	11	800	Total	96,00

Recognition accuracy was then evaluated for different sampling frequencies between 1 Hz to 82 Hz. It could be shown, that for sampling rates below 12 Hz recognition of movement patterns was not successful (Fig. 4).

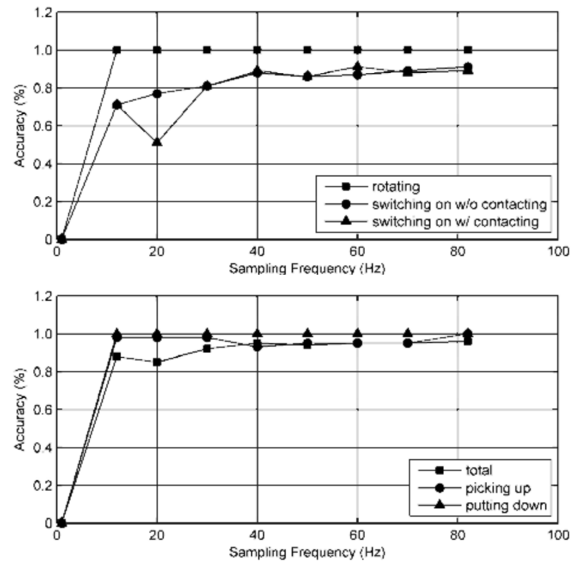


Figure 5. Recognition of movement patterns

However, when sampling rates increase above 12 Hz, movements of ‘putting down’ and ‘rotating’ have been correctly assigned with an accuracy larger than 93 % for ‘picking up’ - Since the high frequency ranges of the acceleration signal gets lost with a decreasing sampling rate [12], the recognition performance for switching the drilling machine on with or without work piece-contact decreases. At lower sampling rates these have been wrongly identified as simple ‘movements’.

IX. CONCLUSION AND OUTLOOK

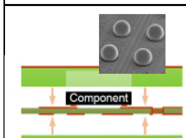
In this paper, an algorithm for the identification of acceleration patterns occurring during human interactions with drilling machines has been presented. Five characteristic drilling activities have been examined in a mock up workshop scenario. Data have been gathered from a single tool-mounted three axis acceleration sensor.

With a suitable combination of techniques of preprocessing of the acceleration signal, feature extraction from the time domain of the signal, classification and post-processing, high classification accuracies have been achieved. At a sampling frequency of 82 Hz, the algorithm performs with an overall accuracy of 96 %, with an accuracy of 100 % for picking up; putting down and rotating the drilling machine. For patterns such as ‘putting down’ even further opportunities arise with respect to the realization of low-power sensor systems with reduced sampling rates.

The presented sensor functionalities are currently implemented in advanced MST setups focusing on size reduction and minimized power demand (Tab. II).

 ISBN: 978-1-61208-425-1

TABLE II. FURTHER GENERATIONS OF MST STRUCTRES REDUCING SIZE AND POWER DEMAND

	**V1** - Arduino based sensor node with custom layers *Purpose*: Functional demonstrator for further specification of MT requirements *Function*: Low resolution temperature sensing, acceleration, ID, communication (Bluetooth) *Technology*: Commercial sensor platform, customised sensor layers *Power consump.*: 110mW in active mode; continuous operation
	**V2** – Custom sensor node with optimized circuitry *Purpose*: Evaluation of design approach, debugging, circuitry optimization *Function*: Precision temperature sensing, 3D acceleration, orientation (compass), identification, optical indication of active status, RF-communication (2,4GHz IEEE 802.15.4) *Technology*: PCB, 4-Layer, one-sided SMD assembly *Power consump.*: 58mW in active mode, 30µW in advanced deep sleep mode; Net power consumption 100µW-500µW depending on duty cycle
	**V3** – Mini. sensor using advanced packaging tech. *Purpose*: Demo. of miniaturisation potentials *Technology*: Size-optimized routing; embedded active and passive devices, bare-Die assembly *Function & Power consump.*: as V2

ACKNOWLEDGMENTS

This work was funded by the Deutsche Forschungsgemeinschaft (German Research Foundation) within the Collaborative Research Centre (SFB) 1026.

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