A SENSOR DESIGN AND DATA ANALYSIS FOR AUTOMATIC DRUM BEATER WINDING

Zhao, Yuchen (1); Johson, Teegan (2); Goh, Yee Mey (1)
1: Loughborough University, United Kingdom; 2: Cranfield University, United Kingdom

Abstract

In the percussion music industry, drum beater manufacturing requires a skilled operator to manually wind the beater with acrylic yarn. Tacit skill is used to control and adapt tension during the winding process of beater construction, which cannot be easily articulated. Consequently the operator has been unable to successfully pass the skill on. In order to overcome this problem, an investigation into automating the drum beater winding process has been initiated. An in-depth human task analysis was performed to identify the skill-, rule-, and knowledge-based tasks during the winding process. In this paper, the two key parameters, yarn tension and patting force reported by the human task analysis during the manual process are further studied. The patting force has been measured and analysed for the low-level control unit. A tension measurement sensor has been designed and substrate has been simulated. This sensor will be used to measure yarn tension during the manual winding process and further work will be carried out to analyse the results for tension control mechanism.

Keywords: Design methods, Sustainability, Human behaviour in design, Simulation, Measurement

Contact:
YuChen Zhao
Loughborough University
Intelligent Automation
United Kingdom
y.zhao@lboro.ac.uk

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1 INTRODUCTION

Beater construction for percussion musical instruments is largely procedural, however within the winding section of construction, a combination of procedural and tacit knowledge is used. This tacit knowledge is seen in the use and modulation of tension while winding the yarn around the beater head (shown in Figure 1). Procedural knowledge can be easily communicated and written down; tacit knowledge on the other hand reflects accumulated experiences, ways of knowing and cannot be easily communicated (Woods and West, 2010). This tacit skill is relatively difficult to maintain and replicate by another trainee. The current workforce is due to retire with no possibility for replacement, therefore an automatic solution of this winding process is needed to ensure the business is sustainable in the near future.

Figure 1. Example of manual process in series

From our research, the closest automated flexible yarn winding technology we can find is for cricket ball winding (Van Asselt, 2006). This technology cannot meet the particular quality standard due to the fundamental geometrical constraints. In order to replicate the flexibility of current manual process, the automation solution should be delivered in active compliant motion scenario using computer control (Lefebvre et al., 2005). Due to the complexity of the process, no passive compliant mechanism will work. The controller in the system diagram (as shown in Figure 2) expects low level control signal for tracking the process states, however learning this reference signal is a research challenge. Therefore the research from human factors (HF) becomes of most value (Caird-Daley, Fletcher & Baker, 2013).

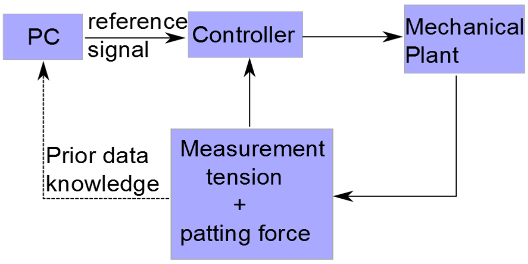

Figure 2. Control system diagram

1.1 Human Factors Analysis

In order to fully understand the process and deliver the potential solutions, a HF investigation was performed to understand the manual work (as shown in Figure 1) using a hierarchical task analysis (HTA) and a task decomposition (TD) (Johnson, 2014). HTA is a method for logical deconstruction of the physical and cognitive components of a task (Kirwan & Ainsworth, 1992). In Johnson (2014), the winding task is systematically decomposed into a structure of overall goal, sub-goals and operations. A TD was then applied to the HTA to extend the data, which breaks the operations from the HTA down further into a number of categories relevant to the research requirement (Kirwan & Ainsworth, 1992). These included; the identification of the sensory cues used by the operator, their associated decisions, actions, performance levels (which applies Rasmussen's (1983 and 1986) skill, rule, knowledge (SRK) framework), critical values, the cause of process variations, likely errors and error correction. A snapshot of the full TD for "wind appropriate number of vertical winds" is shown in Table 1.

Table 1. Example Task Decomposition of Beater Construction

HTA Level		Purpose	Beater Variation				Cues	Decision	Action / Response	Performance level	Potential errors	Potential to correct errors	Critical values	Process variations
			077 soft hard beater	**076 medium beater**	**071 soft beater**	**075 hard beater**								
2.3.1.2	Wind first three winds securing the thread around the beater then let go of the tail and push it up against the underside of the beater so that it is caught in the next winds	Prevent the end from coming loose and consequently all of the winding					Visual: look to check that the winds overlap to ensure that the tail is caught	Has the end been caught? Or has it slipped out from under the thumb?	While winding make sure that there is some overlap while se	**Rule based**	The tail is not caught in the winds	Catch the tail in subsequent winds		
2.4	**Wind appropriate number of vertical winds**	Tidy up the beater head. At top point of the beater, go over the central point of the beater head with the thread.	60. Slower more conscious winding due to less possible winds	70	70	60	VISUAL: look for any gaps in the wind.	Are there any gaps?	Cover any gaps with winds.	**Knowledge based:** monitoring the accuracy of the winds	Gaps are visible in the wind	Look to fill in while wrapping	See variation columns. Beater held vertically. Each wind is wound from the bottom to the top of the beater head.	
							TACTILE: feel for the right level of tension	Are the winds slipping off of the beater?	Increase the tension	**Skill Based:** level of tension to apply and where to wind to prevent winds from slipping off of the beater head				

Two TD categories are of particular importance, firstly the identification of the SRK framework (Rasmussen, 1983, 1986) and secondly the cues. Skilled performance is a preprogramed physical response under minimal conscious attention, which is associated with tacit knowledge (Caird-Daley et al., 2013). Whereas rule based performance includes activities guided by explicit rules and procedures which tend to be stored either in the memory or written in Standard Operating Procedures (SOIs). Finally knowledge based performance involves reasoning out problems and is highly cognitive requiring a high degree of conscious control during task completion. Rule and knowledge performance are explicit and consequently are categorised as procedural knowledge, they are therefore considered easy to automate because all of the steps of the process are fully articulated (Caird-Daley et al., 2013). Skilled performance on the other hand, is difficult to automate because of the difficulty to convert tactic knowledge to explicit knowledge. The identification of both procedural and tacit knowledge helps to classify areas of the task that may hinder or prevent translation of a manual task to an automated one because the intricacies of the task are not fully known. The cues used to carry out tasks, particularly those used during skilled performance can help develop or identify a method of recording a task to capture the skilled activity being carried out and gain information about the decision making that takes place. The rest of the categories identified within the TD are used to fully understand the task and help in the development of the automated solution as a whole.

A high potential for automation is found due to the high proportion of rule and knowledge based operations (Caird-Daley, et al., 2013). From the HTA and TD, the key instances of tacit knowledge identified are the tension maintained on the yarn during winding, and the patting force applied by the thumb to produce a near spherical shape beater. The tension operations are tactile which is very difficult to measure objectively but the operator relied on tacit knowledge to maintain the right levels. Similar difficulties were identified in the patting operation of the task.

1.2 Design Methodology

The design paradigm for intelligent automation/robot mainly includes sensing, planning and acting phase (Murphy, 2000). However, the specific methodologies for each phase of design are not customisable or reusable (Suzuki et al, 2013). Researchers are proposing new methodologies by involving human in the design loop by understanding the manual process (Suzuki et al, 2013). They introduced human modelling based on the hierarchical classification of skills. The classified skills are social skill, planning skill, cognitive skill, motion skill and sensory-motor skill. This provided an efficient way of investigating different level of human skills for designing assistive systems for machine operators. Also, an understanding of human's performance is important when designing an automation solution in order that it can incorporate the correct routines for command and control of the process variables. Currently, the behaviour of industrial robots is mostly rule-based. However, this level of automation is relatively low if the designer wants the robot to become well behaved in a semi-structured or unstructured working environment. The challenges in creating a formal design methodology stem from many reasons: complexities of structuring measurement and control system for process parameters of individual subsystems and the system as a whole (Mikrin et al, 2013);

interaction with a dynamic and unstructured environment (Chella et al, 2009); no standardised rules to transfer the knowledge from understanding the human operator's performance to automation solutions (Suzuki et al, 2013). Therefore, a gap is identified from the literature for an overall design methodology for robot considering the various human skills. A proposed methodology is shown in Figure 3. The most important part of methodology is the knowledge processing unit where the knowledge stored and reused, also where cognitive planning occurs. An example of the knowledge processing unit block can be found in Tenorth et al (2010), which introduces a knowledge processing infrastructure for cognition-enabled robots. The human knowledge can be modelled as a meta-model and stored as an ontology. The robot will reactively plan its motion based on perception (sensors data) and querying its current states. As shown in the figure, the overall methodology is informed by a perception unit and understanding of the human knowledge. This paper, focussed on the tension measurement unit sensor design and patting force analysis for beater winding, aims to bridge the gap and contribute to the knowledge processing unit and the task level controller.

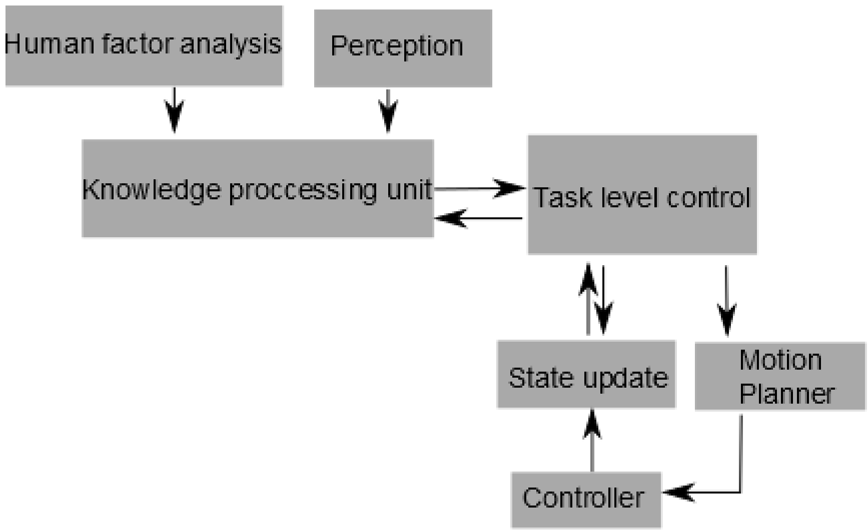

Figure 3. The design methodology for automation system

In this paper, we will develop a tension measurement unit and patting force measurement to complete our understanding of the manual process from human factors studies. One of the most important considerations in this study is ensuring the measurements are done during a continuous winding process. This is to minimise interruptions on the worker as the result will be very different if the operator is asked to stop, then measure and restart. By looking at the product in TMi (2014), three roller configuration (two dummy and one active) is used, however their products are too big for the operator to hold, and they are suitable for retrofitting on lathe rather than on the human hands. To avoid this problem, the sensor must by small and comfortable to be held by the operator whilst performing their task. This requires the selection of a suitable transducer.

Two types of transducers are considered. Linear Variable Differential Transformer (LVDT) (Carlson et al., 1990) sensor is an absolute position or displacement transducer that converts the displacement into proportional electrical signal. It has low hysteresis and high repeatability performance. However, it is very difficult to find the size which can fit our need. Another choice is Strain Gauge (Hoffmann, 1989), which is a device to measure the strain on a substrate. As the substrate deformed, the corresponding resistance change will be measured by the Wheatstone bridge circuit. The advantage of using Strain Gauge is the size of transducer can be small, details will be shown in the next section. The problems of trouble shooting and calibrating the transducer are not included at this design stage. However, the shape and the substrate's material which increases the sensitivity is analysed and a simulation result is discussed later.

The patting force is another critical measurement that needs to be performed. The main problem is the place where the sensor needs to be installed. The sensor we use is Force Sensing Resistor (FSR) (Nikonovas et al., 2004), which returns values that correlate with the pressing force. We record the operator for the whole winding process and analyse the data. The rest of the paper is organised as follow: Section 2 describes the method for measuring and analysing the patting force, including the experimental set-up and initial results. In Section 3 the design of the tension measurement sensor is introduced and simulation results are shown. The conclusions and future work are discussed in Section 4.

2 PATTING FORCE MEASUREMENT AND ANALYSIS

The motivation to investigate the patting force is that it is necessary to maintain the spherical shape of the beater head, which is a unique feature for the company's beaters. From understanding the manual process, it was evident that the operator uses her thumb to apply pressure to the bottom of the beater to maintain its shape, as shown in Figure 4. She held the beater head with two fingers. It is a continuous process, and it is important to perform measurement without disturbing the operator. In order to minimise interruptions, we use a commercially available Force Sensing Resistor (FSR) in our experiment. We also propose an approach to systematically analyse the data, as shown in figure 5. This section details the sensor calibration, then data processing and comparison of the camera recording to arrive at an explanation of the process observed.

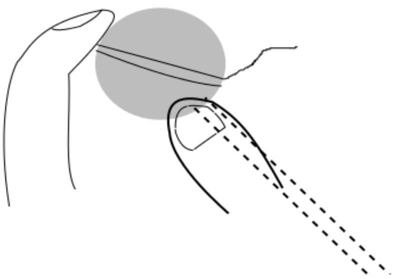

Figure 4. An example of patting behaviour

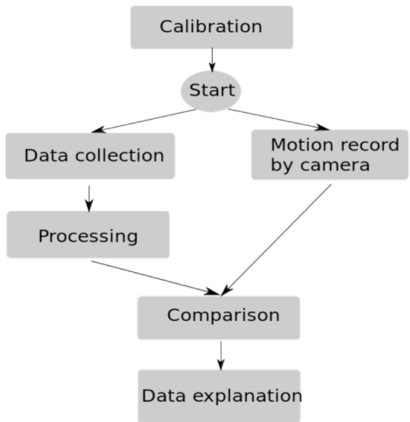

Figure 5. Patting force data analysis process

2.1 Sensor calibration

An FSR is used because it is easy to retrofit. It is essential to calibrate the sensors to indicate force based on a change in the material resistance when force or pressure is applied. The calibration experiment in this paper is shown in Figure 6. The problem is the sensing area of this pressure pad is only 1 cm^2. A solid stainless steel cylinder of 1 cm^2 and known weight plates are used to get around this problem as shown in Figure 6. We select 7 points for the calibration curve (a mapping from intensity to calibrated force level which the maximum value is 15 N) as shown in Figure 7. Here as we can see the relationship between force and resistance is almost linear. The repeatability can be achieved by normalising a number of experimental results. The actual measurement is described in the next subsection.

Figure 6. Calibration experiment components (scale, known weight plates, steel cylinder (Diameter: 1cm^2), pressure pad from Flexi Force (Tekscan,2014))

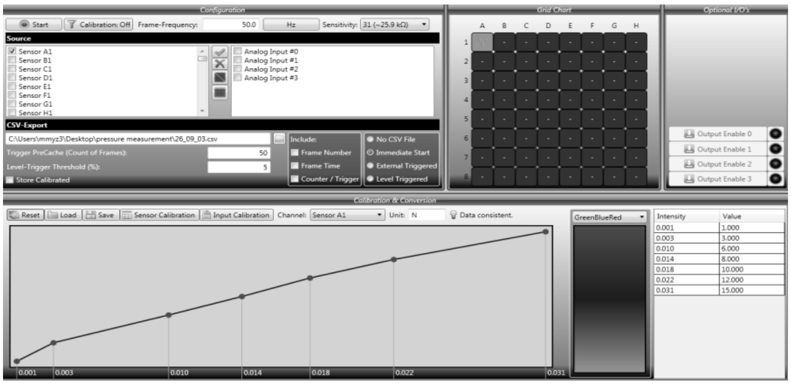

Figure 7. Calibration curve

2.2 Data collection and processing

In this stage, the data collection and camera recording are discussed. The first problem to overcome is to secure the FSR sensor around the thumb such that it is compressed during patting action without interrupting the operator. Therefore we inserted the FSR sensor in a thin glove, and secured the sensing area on the tip of thumb using a double-sided tape. This way, the leads can be led out from the glove and does not disturb the operator. It is acknowledged that the glove will have an influence on the tactile feeling.

The data recorded is noisy. The sampling rate is 50 Hz, therefore more than a thousand data points recorded. A moving average strategy with window size 10 was chosen to filter out the noise and achieve a smoother data set. This means no sampling point is deleted but smoother than original data. The window size is gained by some trial and error, choosing a bigger window size gives smoother data but some detail may be lost.

The next step is to extract the trend of the filtered data. Due to the intrinsic non-linearity of the data, we use the neural network toolbox in MATLAB to regress the data with good generality. As it is shown in figure 8, we performed three experiments with a number of data points in each of those. We trained the each experiment until the performance index, i.e. Regression R value larger than 85% as shown in Table 2. The performance index is a correlation value, which reflects how well the regression between the target and output parameters. Parameters such as number of the cross validation points and shape of kernel function can also be tuned in the toolbox. The general context of the neural network is introduced in (Murphy, 2012).

Table 2. Neural network parameters and performance index

Experiment	No. samples	Training (70%)	Validation (15%)	Testing (15%)	No. Hidden layers	Regression R value		
						Train	Validation	test
1	3809	2667	571	571	30	0.8604	0.8607	0.8697
2	2072	1450	311	311	30	0.8844	0.9017	0.9042
3	1536	1076	230	230	30	0.9154	0.9120	0.9234

As the data fitting result is shown by the **bold** curve (Figure 8), we can roughly recognise the force signal is following some regular pattern, a pulse width modulation signal (PWM). The next step is to compare with the video to validate this result.

2.3 Video recording and comparison

In this stage, the problem to be solved is recognising the force signal and identifying possible winding phases. In each episode of data set, the actual winding process was neither starting from the beginning nor finishing at the end. Thus we need to firstly synchronise the starting point in the data from the video. To simply the task, we choose the best experiment to analyse (the third one) as shown in Figure 9. The full video is 32 s. The force level is vividly changing, but by just considering the peak force in each summit, the average is about 12 N. The sampling frequency is 50 Hz, i.e. 200 samples = 4 s. Therefore, after observing the video, the actual winding starts from 5 s and ends at 30 s. As we can

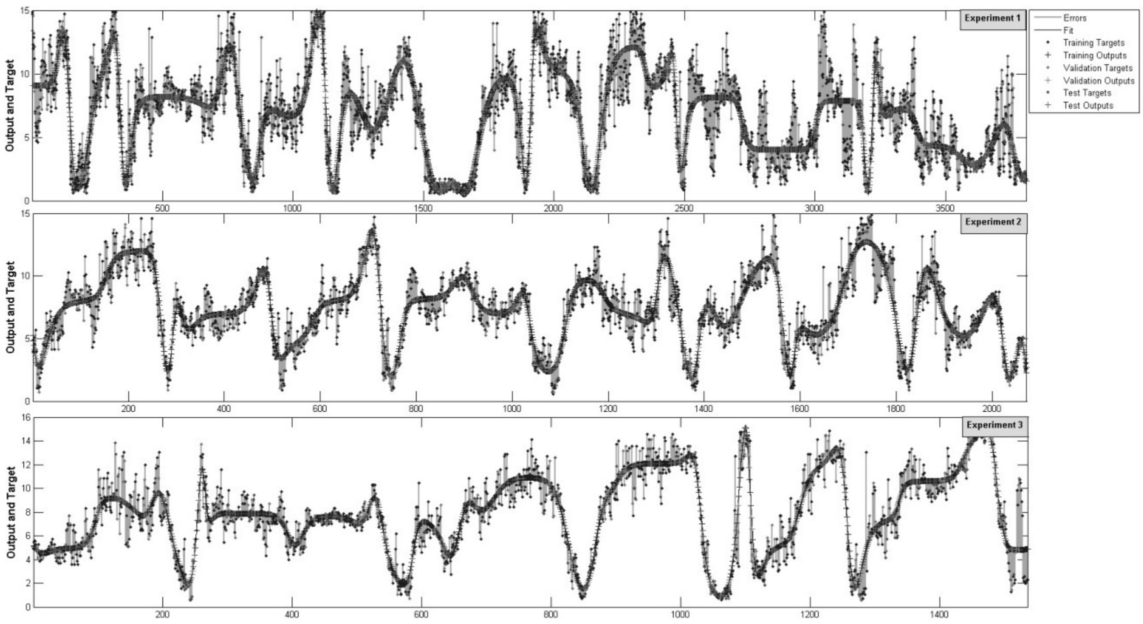

Figure 8. Data fitting result from three experiments

see, from 1000 to 1200 samples, there is a huge drop, however, that is because of some abnormal adaptation by the operation (loss of tactile feeling due to the glove), and therefore, we can fill that valley with the normal force. The reason we assume this is a PWM shape is because each beater has exactly 70 windings and after every 12 windings the beater is rotated. This explains the signal drop at each interval when the thumb is removed temporarily. From this analysis, we identified six intervals, and each one has 12 windings which indicate smaller drops. We further fill the signal with a plateau to simplify the process. From the above analysis, it is reasonable to assume a PWM signal which can potentially be used as a signal input for the controller. And more importantly, we can estimate the phase of winding because we know exactly how many windings are completed within each interval. This can be another source of knowledge to build the controller.

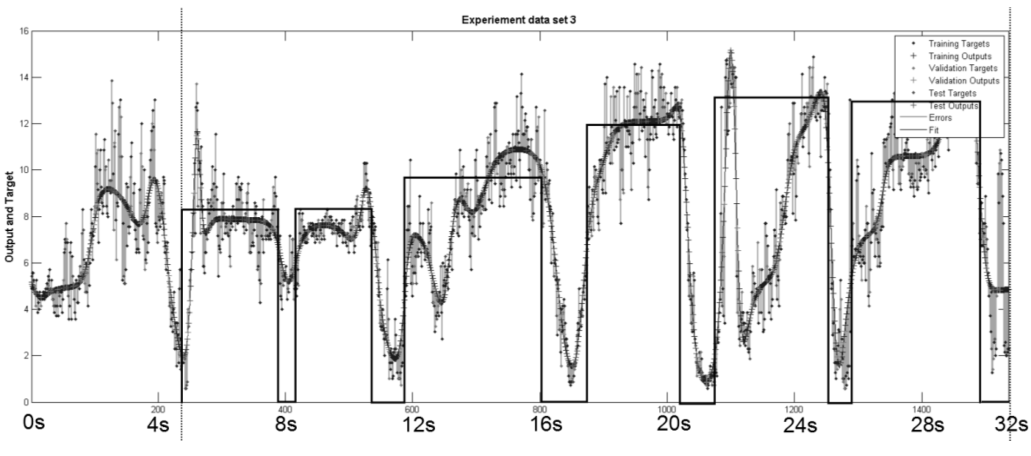

Figure 9. PWM assumption in experiment 3

3 TENSION MEASUREMENT SENSOR DESIGN

This section will explain the sensor design procedure in detail. The first stage contains two elements as shown in Figure 10. The 3 roller concept as discussed in introduction is a popular configuration used in the industry for measuring yarn tension. The major components are the front three rollers attached on the flank: one active and two dummy rollers. The active roller links against the load cell which are fixed in the box. Our design was inspired from this configuration as shown in Figure 11, where the strain gauges were fitted on the beam-shape load cell. However, in order to save space, the two dummy rollers had been replaced by two rods with a hole on each. The initial choice of load cell was a rectangle beam, which is refined in the simulation stage at the latter part of this section.

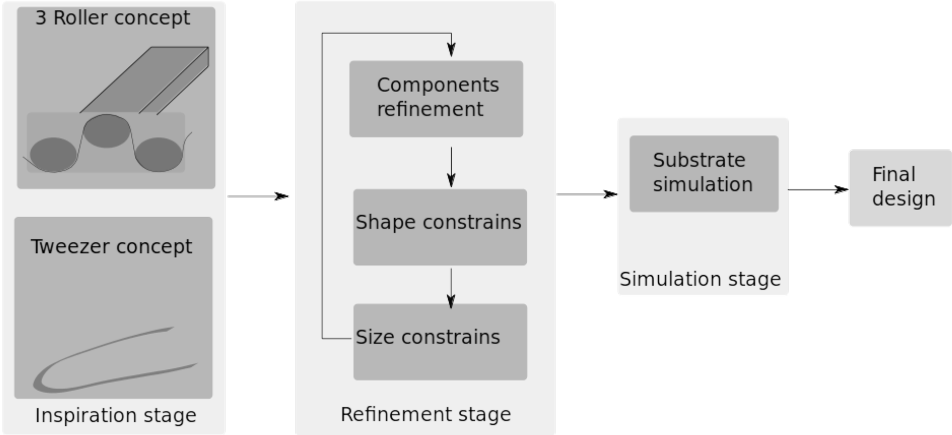

Figure 10. Sensor design stages: Inspiration, refinement and simulation

Another element of the concept for applying pressure was inspired from tweezers. This is because we need a mechanism to imitate how human fingers apply pressure on the yarn. Therefore, the operator instead of directly putting the fingers on the yarn, they press the end of tweezers-like mechanism with rubber band and brake on it as shown in Figure 11.

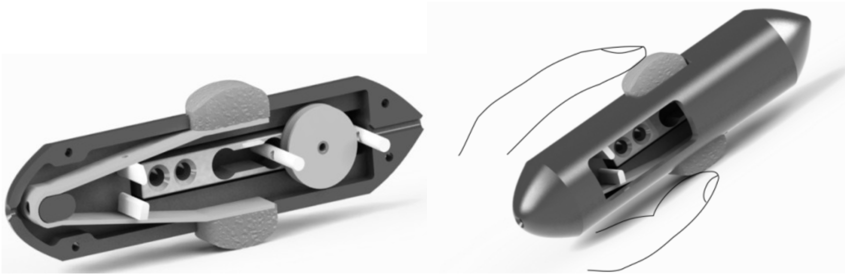

Figure 11. Proposed sensor design (left) and how to hold the sensor (right)

In the refinement stage, every change of design may cause other parts to change too. Therefore, this is an iterative process. For instance, if the space for the interior parts is smaller, the overall size of those parts needs to scale down. However, if a certain part for instance, the roller size, has to have 15 mm diameter, the outer shape design may change as well to leave more space for the roller. In general, there are some rigid constraints for the shape and the size. In this case it is a 3D space. The shape should be smooth to fit the hand size. As the real size of the sensor is small, there are difficulties to find the commercial standard parts. The design was further developed for manufacture and assembly.

After the second stage of design, the space available for the load cell is known. We assumed a primitive shape. In the third stage, we cut out some material in the middle of substrate as shown in Figure 11, and the design was simulated with Finite Element Analysis (FEA) in SolidWorks. The problem to solve in this stage is choosing the right material for the substrate. Before the substrate is chosen, it is worth knowing some context about Strain Gauge.

The Strain Gauge is shown in Figure 12. The length is 3 mm, resistance is 350 Ω, and gauge factor is 2.13. One can find out different configuration of installing Strain Gauge in (Hoffmann, 1989), here we don't need to know the force in multi-axis; therefore, a full bridge is used with normal configuration to compensate for the temperature and increase the range of measurement.

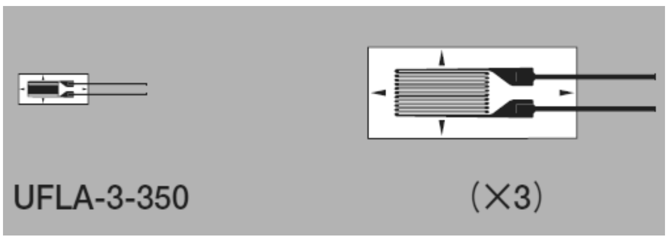

Figure 12. Strain Gauge used in this research

Two common materials are considered as the substrate, namely stainless steel and aluminum. From the simulation result shown in Figure 13, the left two holes are assumed fixed because it will be fixed on the sensor body. The actual force is applied vertically in the right hole, and the contact area is about 49 mm^2. The actual deformation is visually exaggerated in the simulation, which is in the level of µm. The bright area is where the maximum tension or deformation happens. Therefore, we only need to compare the result which returns the maximum strain but also within a tolerance value (< 2%) (Micro-Measurements, 2014). The actual force applied was 13.8 N, which was the breaking tension of the yarn from the previous test. The results are shown in Table 3.
From the result, the deformation rate, the strain in aluminum substrate is larger than the stainless steel but less than the tolerance (2%). Therefore, in this sensor design, aluminum was chosen as the material for the substrate. This sensor will be manufactured and used to measure yarn tension during the winding process.

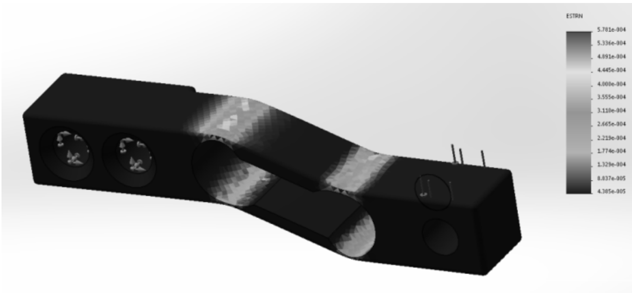

Figure 13. An example of the simulation result for the substrate (brighter color means more strain and deformation)

Table 3. Simulation results of two types of materials

Material	Yield strength (MN/mm^2)	Length (mm)	Area (mm^2)	Maximum Strain	ΔL (µm)
Aluminum	27.6	50	49	0.13%	65
Alloy Steel	172.4	50	49	0.05%	25

4 CONCLUSIONS

In this paper, we are able to integrate human in the automation design methodology by analysing data and sensor design according to the HTA and TD from human factor research. The measurements and sensor design can potentially provide valuable and additional information which HTA doesn't give. Firstly, the patting force measurement was analysed to understand the human operator's method to maintain beater shape. This force signal was further simplified to some pulse width modulation signals. The importance of this signal is that it can be directly used for the low level controller to follow. This is the translation procedure mentioned early in the active compliant motion, where the high-level symbolic primitive (from human knowledge) is translated into low-level control primitives. The future work of this part of work is to use more experiments to validate the results. Secondly, a hand-held tension measurement sensor was designed. This sensor will be used to collect the time series data from a human operator and understand the tension levels and process features/phases. This is also the immediate future work after this stage of research. Since the winding process requires operator's tacit knowledge to execute, only after understanding the manual process that an automation solution can be delivered successfully. This paper, at this stage, is one forward step towards that goal.

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