



# Digitisation of manual composite layup task knowledge using gaming technology



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## ABSTRACT

Increased market demand for composite products and shortage of expert laminators is compelling the composite industry to explore ways to acquire layup skills from experts and transfer them to novices and eventually to machines. There is a lack of holistic methods in literature for capturing composite layup skills especially involving complex moulds. This research aims to develop an informatics-based method, enabled by consumer-grade gaming technology and machine learning, to capture and digitise manufacturing task knowledge from skill-intensive hand layup. The digitisation is underpinned by the proposed human-workpiece interaction theory and implemented to automatically extract and decode key knowledge constituents such as layup strategies, ply manipulation techniques, motion mechanics and problem-solving during hand layup, collectively categorised as layup skills. The significance of this research is its potential to facilitate cost-effective transfer of skills from experts to novices, real-time automated supervision of hand layup and automation of layup tasks in the future.

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## 1. Introduction

The demand for goods made out of composite materials is ever increasing in aerospace, automotive and sports equipment sectors. This is because composite materials exhibit superior qualities (e.g. a carbon fibre reinforced polymer is up to 5 times stronger than steel 1020 while weighing only a fifth), have high corrosion and fatigue resistance and provide high product-design flexibility [1]. Increased demand has resulted in growing pressures on the composite industry to increase production volumes, speeds and productivity while maintaining high product quality. However, the very properties of the composite materials that make them superior are also responsible for making them difficult to mass produce [2]. The manufacturing process involves hand layup of stacks of woven composite plies pre-impregnated with resin on to an intricate mould to form complex shapes without leaving any air gaps between the mould surface and the ply. Moreover, different

composite materials exhibit different deformation mechanisms depending on the direction of the ply and the pattern of the weave. This multifaceted relationship between the geometry of the mould, the deformation characteristics of the ply and the ply manipulation techniques is a knowledge that is possessed by experienced laminators [3].

Manual layup remains a significant part of the composite industry despite its low production speeds and discrepancies in quality caused by human variation. However, it is becoming increasingly difficult to sustain because of high process costs, dwindling number of skilled laminators and the gestation periods to acquire expert layup skills. At the same time, automating the layup is difficult because the inherent knowledge about the process is not explicitly available [4]. To reinforce this point, in the review of the engineering aspects of automated prepreg layup, Dirk et al. have observed that the commercial automated layup systems such as Automated Tape Laying (ATL) and Automated Fibre Placement (AFP) are developed by industrial machine companies with either none or limited background in the composite industry and are currently building up their composite layup expertise [5].

There are a few related studies in literature that have attempted to understand the manual layup process. Most recently, Elkington

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et al. [6] have presented a detailed study of the approach and techniques used by laminators of varying layup experience while manipulating pre-impregnated woven composite plies onto complex mould shapes. Using visual observation of video footages, specific hand gestures and ply manipulation techniques used by the laminators were identified and documented. Kikuchi et al. [7,8] have presented a motion analysis method to extract tacit knowledge, such as expert hand gestures and eye movements, during a hand layup and spray coating process and their relationship with mechanical properties and dimensional stability of the resulting composite samples. In other recent studies in extraction of human skills, Gu et al. [9] have developed a skill acquisition method that uses a single RGB-D camera to capture human demonstration of a simplified toy assembly task. The method can recognise the part involved, the actions used and estimate the assembly states to generate an assembly skill script for robot learning. Yoshida et al. [10] have used field-oriented interviews and video analysis to extract and compare hand movements during a manual whetstone polishing task performed by skilled technicians and novices. In recent research in human action recognition and extraction from a manual task, Tang et al. [11] have used depth imaging and extraction of variability between different depth image modalities and pre-defined action datasets. Chen et al. [12] have used a combination of depth camera and inertial sensors strapped to the human's body to extract and analyse human actions during a manual task. Han et al. [13] have provided a detailed study of manufacturing task analysis by comparing the capabilities and limitations of different motion sensing technologies using depth imaging such as the Microsoft Kinect, Leapmotion and Senz3D. The more traditional approach of experimental derivation of manufacturing knowledge of layup tasks is demonstrated by Kim et al. [14] and Lightfoot et al. [15]. Kim et al. reported the study of material characteristics, layup accuracy, and thickness variations recorded during the continuous tow shearing (CTS) layup technique using microscopic observation of impregnation quality, tow path tracing using image analysis to gauge layup accuracy and CT scanning to measure thickness variation of the manufactured specimen. Lightfoot et al. studied the mechanism of shear force based wrinkle formation during hand layup due to ply slippage as well as mismatches between the thermal characteristics of the composite material and tool.

The above studies have been able to capture information about the specific techniques involved in the manual tasks at specific times but fail to extract the expert's overall task strategies as well as provide a medium to conduct real-time automated task supervision and a guide to automate the manual tasks. Moreover, the knowledge about these techniques is limited to the expert's hand and eye movements without considering how the other parts of the body may have contributed to the techniques. Also, the real-time effects of these techniques on the workpiece are not simultaneously tracked thereby making the association of human actions to workpiece progress a near impossible affair. Another disadvantage of these studies is that the knowledge extracted is limited to the process runs that have been directly observed and human response to unobserved/unforeseen process scenarios cannot be anticipated. Finally, the methods proposed are highly specific to the concerned manufacturing task and the task-recording set-up and therefore are not generic enough to capture knowledge from other manual industrial tasks.

This article presents a cohesive and holistic process for digitisation of manual manufacturing task knowledge based on the proposed human-workpiece interaction theory. In this work, innovative informatics methods using gaming technology, such as the Microsoft Kinect, and using machine learning such as Hidden Markov Modelling are used to capture and digitise important constituents of manufacturing knowledge embedded within any manual task involving a human and a workpiece, which in this study is the manual composite layup task. The Kinect is used because it provides a robust and low-cost way of obtaining human motion capture as well as object recognition and tracking from infra-red (depth) and colour imaging [16].

The knowledge constituents of interest in the composite layup task are: (i) layup strategy, (ii) time taken per sub task, (iii) precise human motion, (iv) ply manipulation techniques, (v) mechanics of the laminator's motion during task execution, and (vi) problem solving approach used to correct layup errors. These constituents collectively categorised as layup skills are thus captured and digitised to enable skills transfer from expert laminators to novices, to facilitate real-time automated supervision of manual tasks as well as eventual automation of the manual task. Researchers from the value-creation domain can subsequently develop technology

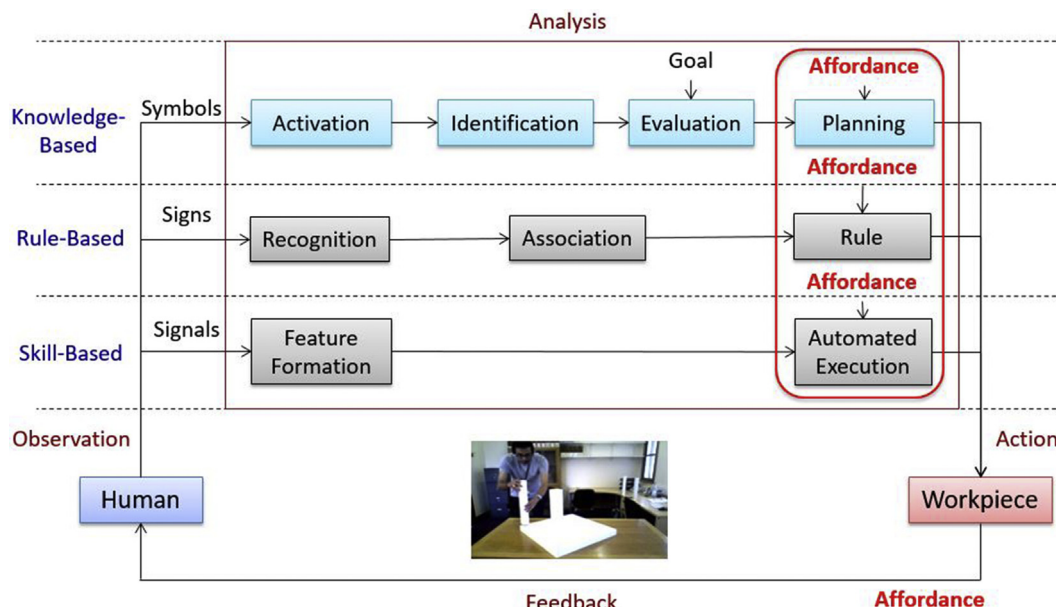


Fig. 1. Human-workpiece interaction theory.

strategies that companies can use to extract value and capture profits from digitised knowledge assets, such as the above for composites manufacturing, as illustrated by Kyläheiko et al. [17].

## 2. Method

### 2.1. Underlying human-workpiece interaction theory

The concept of human-workpiece interactions proposed by Prabhu et al. [18] states that any manual manufacturing task involving a human and a workpiece can be considered as a series of human-workpiece interactions in which every human action is followed by feedback from the workpiece on its state of progress. This feedback is analysed by the human on the fly to choose and execute the next action on the workpiece to channel it towards successful completion. Successive such iterations, some of which may include problem solving, take the workpiece from its initial state to final desired state.

The above theory however is rudimentary in nature, as it does not completely represent human response to different task scenarios. This research is of the view that human response during a task changes according to the way in which workpiece feedback is analysed. Therefore, in order to advance the theory, three seminal theories from literature that are popularly used to analyse human behaviour in industrial settings, namely, Rasmussen's Skill-Rule-Knowledge (S-R-K) framework, Rasmussen's Decision Ladder and Gibson's theory of object affordances are used with relevant adaptations to suit the basic theory (Fig. 1) [19–21].

In a manual manufacturing task there are periods in which human actions on the workpiece are repetitive in nature and are largely governed by muscle memory. This is *skill-based* human response in which workpiece feedback is subconsciously processed as signals. A task is typically associated with a standard procedure for normal execution. The human response when following the standard procedure is *rule-based* in which workpiece feedback is observed consciously as signs that direct the human to pick appropriate rules to apply while choosing actions during the task. Sometimes when unforeseen problems occur during a task, a standard solution is not available. In such cases, the human

response is *knowledge-based* in which the human uses his/her knowledge accumulated from past task executions to solve the problem. This is the adaptation of Rasmussen's S-R-K framework to the human-workpiece interaction theory.

A detailed approach to understanding human problem-solving behaviour during the knowledge-based response is needed. Rasmussen's Decision Ladder concept is used to understand the human's approach as a 4-step process. The human detects a problem with the workpiece by observing its feedback as a symbol that represents the problem, e.g., a wrinkled ply surface after layup. This activates the problem-solving response which begins by identifying the problem and its underlying cause, evaluating the various solutions at the human's disposal and selecting the most appropriate one by keeping the overall task goal in mind, and finally planning the actions within the chosen solution for execution.

Finally, human action on the workpiece at all the 3 response levels depends on the state of the workpiece, which is continuously observed during the task. According to Gibson, an object's affordances are action possibilities available to a human to execute on

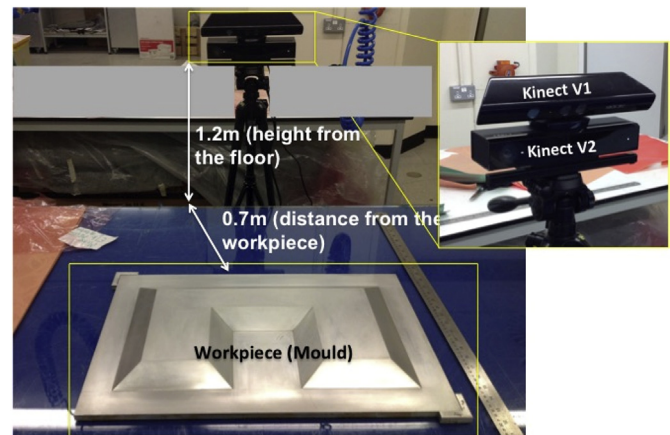


Fig. 3. Task capture setup using two Kinect sensors.

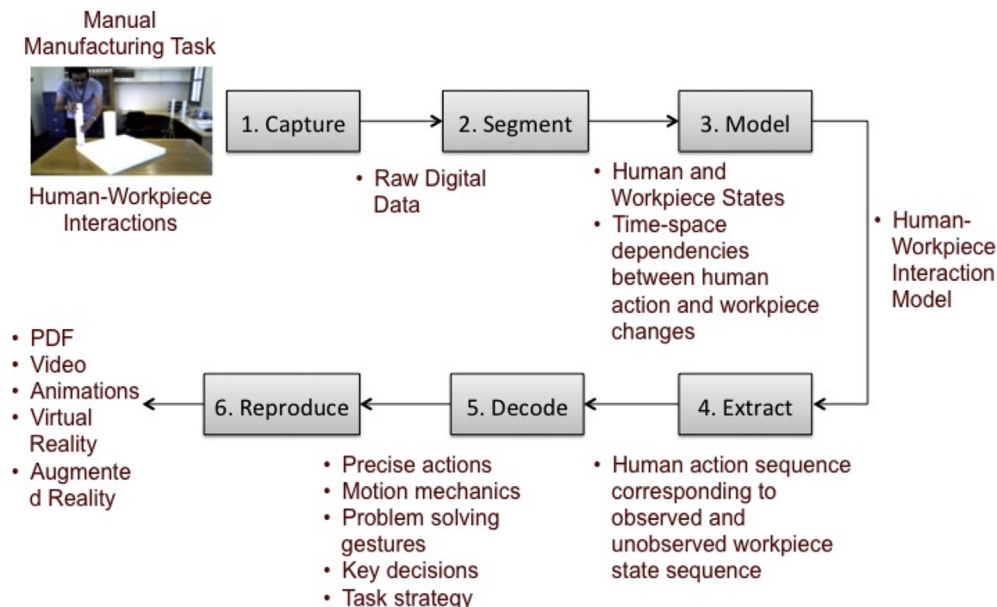


Fig. 2. 6-Step Digitisation process.



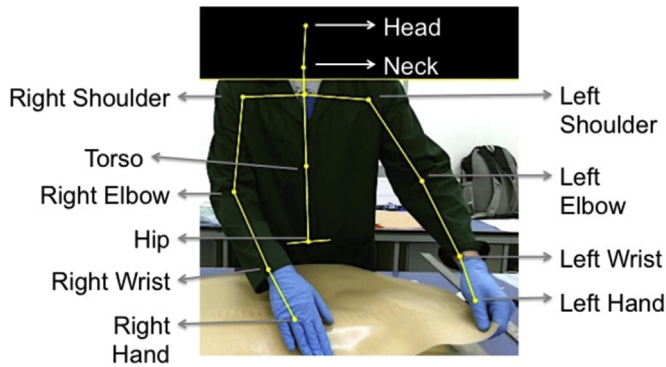


Fig. 4. Laminator's skeleton being tracked during the task.

that object depending on his/her action capabilities. Therefore by adopting Gibson's theory it can be noted that every workpiece

feedback conveys a set of affordances to the human who selects the most appropriate one depending on his abilities, the task situation and the response level at which he/she is operating.

## 2.2. Digitisation process

The digitisation process is underpinned by the above advanced human-workpiece interaction theory and is designed to extract and decode manufacturing knowledge constituents of a task that belong to the skill, rule and knowledge based levels. The data flow within the process follows the standard informatics data flow, namely, data input, data processing, data storage and data output. The resulting digitisation process comprises 6 sequential steps, namely Capture, Segment, Model, Extract, Decode, and Reproduce (Fig. 2).

Step 1) Capture: This is a critical first step whose reliability and accuracy determines the eventual success of the digitisation process of the manual composite lamination task. The main objective of this step is to acquire the actions of the laminator during the

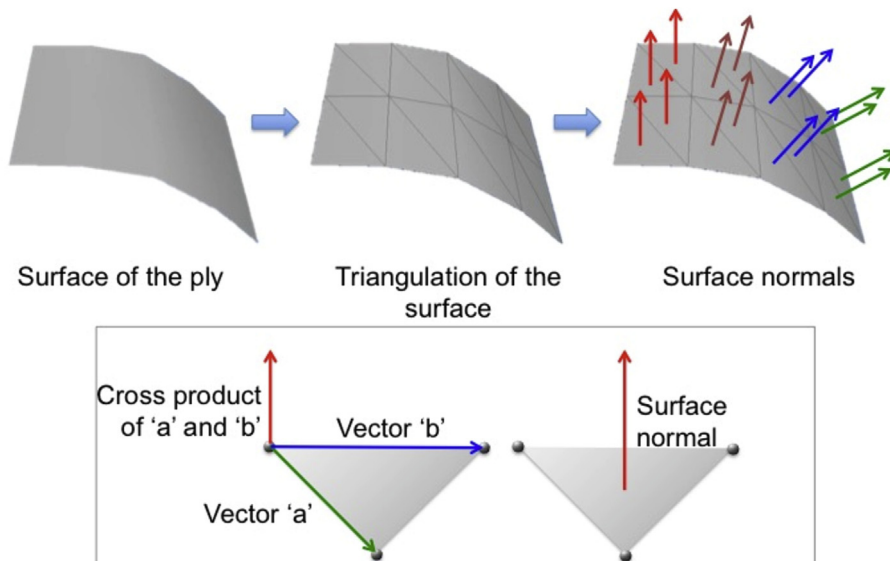


Fig. 5. Tracking ply orientation by computing surface normals of the finite triangular elements.

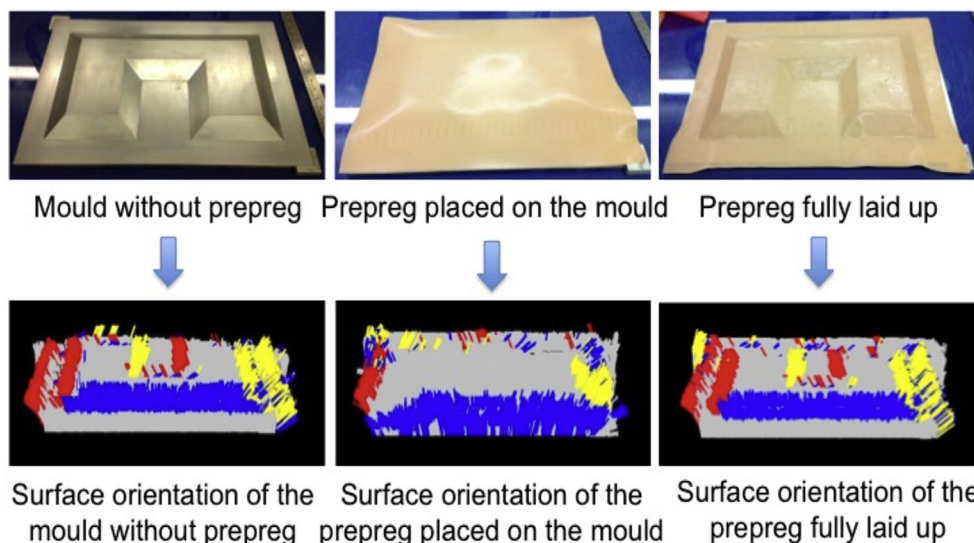


Fig. 6. Capturing workpiece progress by tracking ply surface orientation and comparing against that of the bare mould.

layup process and the effects of those actions on the workpiece (composite prepreg ply draped over the metallic mould) into digital data. The vital requirement and the key innovation in this step is to simultaneously acquire digital action and effect data in real-time so that the action-effect relationships within the task can be established in the subsequent steps using the common data acquisition timestamps.

The key and unique focus of this work is to use consumer-grade gaming technologies for data acquisition. Within this focus, there are three main methods to acquire laminator's action data during the layup task. The first method is to use high-end fixed motion capture systems such as the OptiTrack [22], which captures human motion by tracking markers attached to the human body. This method is not suitable to capture manual tasks in manufacturing settings because it requires installation of multi-sensor localisation infrastructure in each area of task capture on the shopfloor, making it an expensive piece of kit to own and operate. Secondly, apart from the inconvenience of attaching markers on the laminator's body, such systems are tailored to accurately capture human motion but are not designed to recognise objects and track deformation in objects in real-time. The second method is to use inertial sensors, such as accelerometers [23] and attach them to the laminator's body in order to obtain 3D position and orientation data of the human body joint during motion. Even though these sensors are affordable and provide accurate motion capture data, the entire system including data acquisition and communication modules are not fully portable apart from being intrusive for the laminators during the layup task. Wireless inertial sensors are also available such as Perception Neurons [24], but the body kit comprises cables that connect the sensors to the wireless communication module thereby not making any significant improvement in reducing intrusiveness. Also, inertial sensors cannot provide data on how the

workpiece deforms as a result of the laminator's actions and hence another camera-based solution including image processing for object recognition is needed. The third method, chosen in this work, is to use depth imaging based portable, markerless and low-cost motion capture solution, such as Microsoft Kinect, which not only provides reliable human skeletal motion data but also RGB and depth image streams which can be used for 3D object recognition and tracking in real-time.

In the 'Capture' step, Kinect sensors capture the human-workpiece interactions involved in a composite layup task performed by an expert laminator in a 20 °C clean room environment at the University of Bristol's Advanced Composite Centre for Innovation and Science (ACCIS) (Fig. 3). The workpiece is a 600 mm × 400 mm stainless steel mould with varying surface ramp angles and features. The laminator drapes a plain-woven glass fibre ply pre-impregnated with resin onto the mould. Six runs of the layup task are captured including two in which the laminator has solved simulated layup problems. The task captures were conducted in accordance to the University of Bristol's policy for experiments involving human participants.

The laminator's actions during the task are captured using the standard skeletal motion tracking provided by the second generation of the Kinect sensor (Kinect V2). The 3D coordinates of the 12 skeletal joints belonging to the laminator's upper body are tracked at the rate of up to 20 times per second and recorded in a spreadsheet along with the tracking timestamps in seconds (Fig. 4).

Simultaneously, the workpiece progress is tracked by the 1st version of the Kinect sensor (Kinect V1). The Kinect V1 is used because it is not possible to operate two Kinect V2 sensors at the same time on the same computer. An innovative and effective method is proposed to track the deformations on the composite ply as it is pressed down on to the mould during the layup task. Workpiece progress is tracked by obtaining the orientation of the ply and comparing it continuously with that of the surface of the mould underneath. The surfaces of the ply that have the same orientation as that of the contours of the mould surface are considered to be fully conformed and laid up. The conversion of the ply from non-conforming to conforming can be captured by dividing its surface into finite triangular elements and tracking the orientation of these elements in real-time by computing their surface normals (Fig. 5).

The surface normals are then grouped and displayed in different colours depending on their orientation with respect to the unit vectors along x, y and z axis. This way, the surface orientation of the ply can be visualised as either being conformed to the mould surfaces underneath or not (See Fig. 6).

The workpiece progress is recorded as running numbers from 0 (ply placed over the mould) to 7 (fully laid up ply) according to when the layup process is completed in a sequence across the seven workpiece sectors as identified by the laminator (Fig. 7).

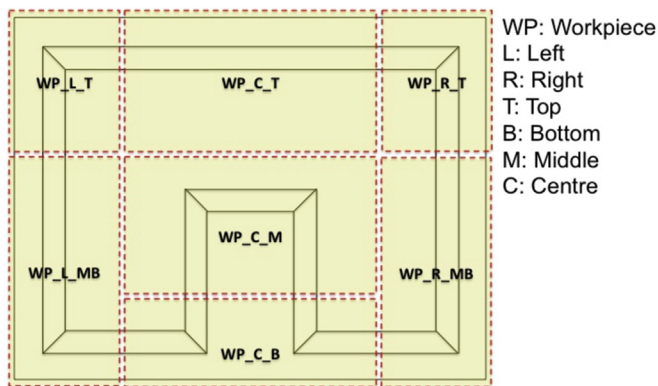


Fig. 7. Seven sectors of the workpiece (mould) named according to their position on the mould.

Table 1  
Segmentation of continuous human action and workpiece data according to workpiece progress.

Time (s)	Timestamp (s)	Frame_No	WP_Progress_State	Head_X	Head_Y	Head_Z	Left Hand X	Left Hand Y	Left Hand Z	LH_Elbow_X
50.6	50.6	441	0	1166	254	729	894	873	778	910
50.7	50.7	442	0	1208	201	754	891	848	792	918
50.8	50.8	443	0	1242	141	799	901	782	815	936
51.0	51.0	444	0	1236	119	873	910	741	826	937
51.1	51.1	445	0	1194	106	968	905	686	913	926
51.2	51.2	446	0	1133	109	1083	913	678	1041	897
52.3	0.8	470	1	973	71	1176	895	712	1022	785
52.4	0.9	471	1	997	69	1157	912	724	995	802
52.5	1.0	472	1	1032	66	1132	932	738	947	824
52.7	1.2	473	1	1078	64	1088	955	778	859	855
52.8	1.3	474	1	1102	65	1061	956	790	832	871
52.9	1.4	475	1	1129	69	1026	981	823	805	899

The workpiece progress is recorded in the same spreadsheet alongside the human action data with the corresponding timestamps. This way specific human action that is responsible for specific workpiece progress can be identified.

Step 2) Segment: The main objective of this step is to segregate the continuous human action data acquired in step 1 into action primitives where each primitive has a notable effect on the progress of the workpiece in the manual layup task. Thus continuous human action and workpiece progress data is segmented into discrete human action states and workpiece states. In literature, motion capture data segmentation has been addressed by considering the human motion data as stand-alone for purposes such as behaviour analysis, ergonomic analysis and activity recognition. Stand-alone motion capture data segmentation has been reported using methods such as filtered sub-space clustering [25], K-means algorithm [26], kernelised temporal cut method [27], and recently low-level temporal segmentation followed by hierarchical clustering [28].

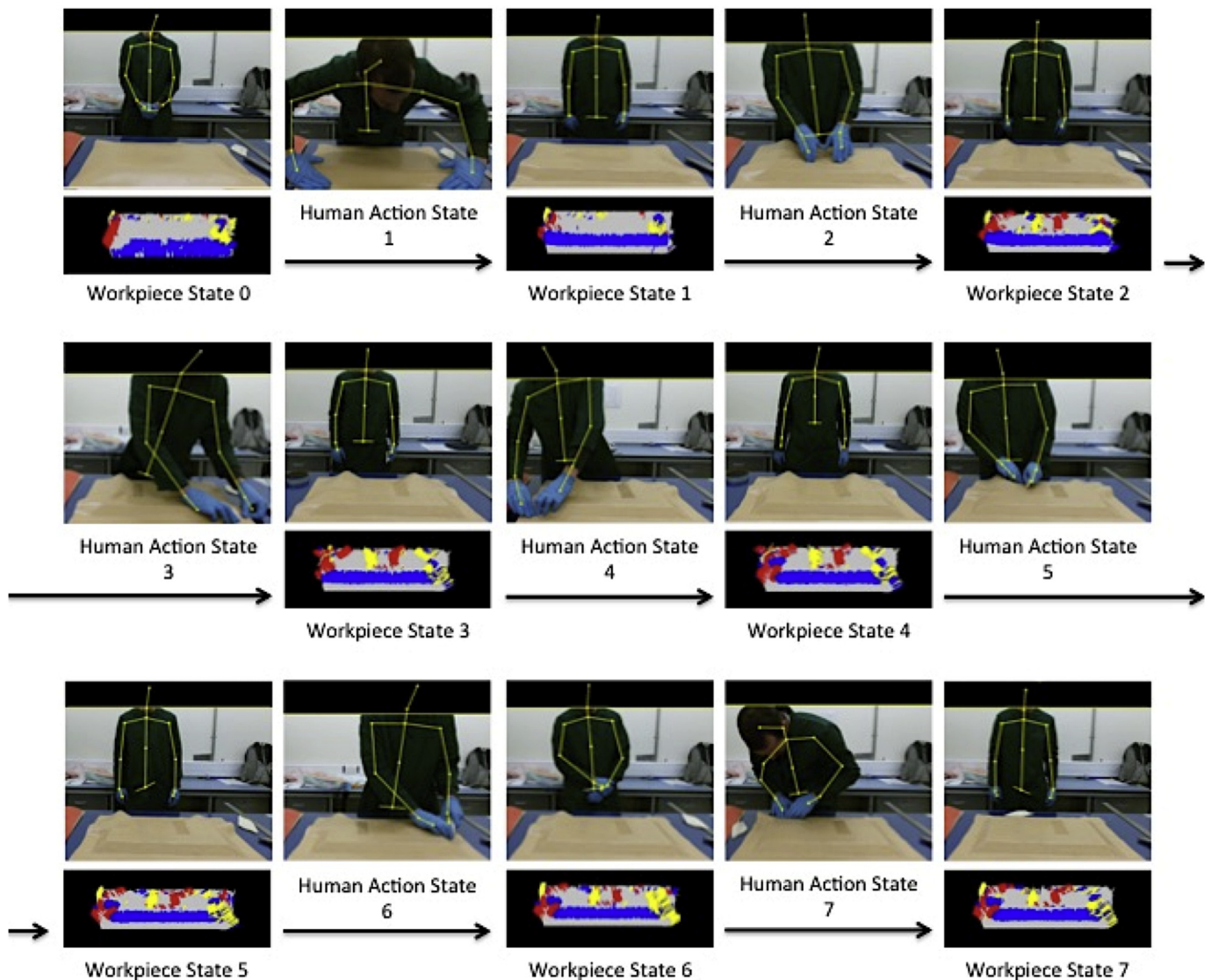
These methods, though successfully applied to segment motion capture data into distinct human action, cannot be applied in this work. This is because a manual layup task involves close interdependency between the human action on the workpiece and the

progressive change in the workpiece with workpiece change being the primary driving factor behind the human action. Therefore, segmentation of human action is made more effective by segregating the continuous human action data at points where the layup task on the workpiece progresses from one sector to another (Table 1), i.e. when one sector of the mould is completely laid up and the next one is attended to.

Even though the human action states are considered discrete, each state is a set of continuous skeletal motion data, which contributes to changing the workpiece state (Fig. 8). The nomenclature of the states is given in Table 2.

**Table 2**  
Discrete human action and workpiece states.

State Sequence	Human Action States	Workpiece States
1	H_C_T	WP_C_T
2	H_C_M	WP_C_M
3	H_R_T	WP_R_T
4	H_L_T	WP_L_T
5	H_C_B	WP_C_B
6	H_R_MB	WP_R_MB
7	H_L_MB	WP_L_MB



**Fig. 8.** Discrete human action and workpiece states.





individual experts that perform the manual layup task. A novel and effective way of modelling human-workpiece interactions using HMMs is proposed in which the workpiece states that are conspicuous are considered observable whereas the human action states that have implicit skills embedded within them, even though the actions themselves are conspicuous, are considered hidden. This way, the interdependency between the human actions and the workpiece states are completely modelled within a single HMM rather than separately.

The HMM is defined as  $\lambda = (\pi, A, B)$  with discrete states  $S$  and  $O$  where  $S = \{s_1, s_2, \dots, s_n\}$  is a finite set of ' $n$ ' human action states (hidden states),  $O = \{o_1, o_2, \dots, o_m\}$  is a finite set of ' $m$ ' workpiece states (observation states),  $\pi = \{\pi_i\}$  are the initial state probabilities,  $A = \{a_{ij}\}$  is the state transition matrix where  $a_{ij}$  is the probability of human action state  $i$  transitioning to state  $j$ ,  $B = \{b_i(o_k)\}$  is the emission matrix where  $b_i(o_k)$  is the probability of observing workpiece state  $O_k$  at human action state  $i$ . It is assumed that the state machine emits an observation and starts to jump to a new state at the same time. Time  $t$  is discrete and starts with  $t = 1$ . The probabilities in the two matrices are time invariant.

Out of the six task runs performed by the laminator, four are uneventful and nearly identical while two include a scenario each where a wrinkled ply surface during the layup was corrected. Therefore, two distinct HMMs are constructed;  $\lambda_{T1}$  for the normal task scenario and  $\lambda_{T2}$  for the problem-solving task scenario. The probabilities  $a_{ij}$  and  $b_i(o_k)$  are assigned heuristically with inputs from the laminator and on observing multiple runs of the layup task performed by the laminator (Table 3 and Table 4).

HMM  $\lambda_{T1}$  captures how the expert laminator performs the layup task routinely on the chosen mould. This model represents the laminator's actions and the effects of those actions on the ply layup on the mould. The human action states and the workpiece progress states listed in Table 2 and their interdependency is modelled within  $\lambda_{T1}$ .

HMM  $\lambda_{T2}$  represents how the expert laminator solves the problem (wrinkled ply) that occurs in the state 2 ( $H\_C\_M$  now named  $H\_C\_M\_P$ ) in 3 steps, namely,  $H\_M\_PS1$ ,  $H\_M\_PS2$ , and  $H\_M\_PS3$  to restore the task back to the correct state  $H\_C\_M$ .

It must be noted that the probabilities in the above HMMs are heuristically obtained and may not be the most optimum values. Though there are two commonly used methods to optimise these probabilities, namely, 'Viterbi' and 'Baum-Welch' training algorithms [36], in this research the Baum-Welch algorithm is preferred

**Table 5**

Layup time taken in workpiece sectors.

State	Time taken (s)
W_C_T	51.5
W_C_M	113.6
W_L_T	30.6
W_R_T	38.4
W_C_B	28.1
W_L_MB	92.8
W_R_MB	100.9

due to its robust and exhaustive nature. However for these HMMs, the Baum-Welch algorithm did not advance past the first iteration implying that the probabilities assigned are reasonably true to the task scenarios being modelled.

This research believes that the two HMMs  $\lambda_{T1}$  and  $\lambda_{T2}$  collectively represent the expert laminator's manufacturing knowledge that is embedded within the execution of the layup task thereby realising a way to digitise this task knowledge and its constituents. The last 3 steps of the digitisation process that enable the extraction, decoding and reproduction of task knowledge are described in the next section.

### 3. Results and discussion

The HMMs that represent the layup task are queried with a given task scenario to extract, decode and reproduce the manufacturing knowledge constituents belonging to the task. The standard methods/algorithms reported in literature to query or analyse hidden Markov models are used in this work without any modifications. However, the way in which these standard algorithms are used to extract and decode key constituents of knowledge used by the expert laminators during the manual composite layup task are new and are described below.

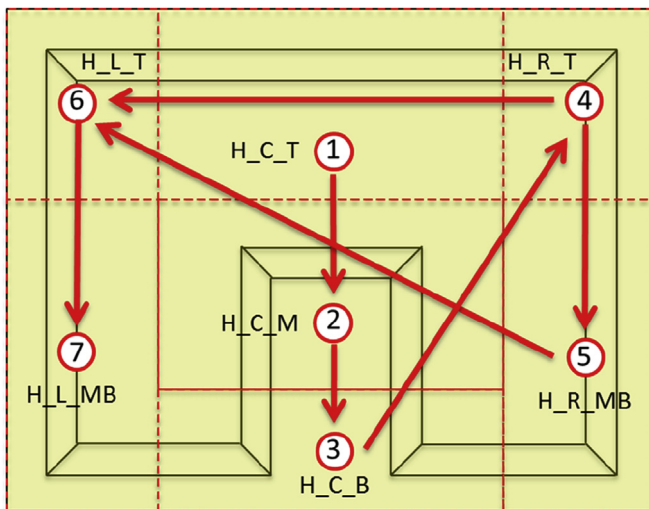
Step 4) Extract: The main objective of this step is to obtain likely human response for any given task scenario, not just the captured ones, thus extracting the task knowledge possessed by the laminator which was used in the layup task. The task scenario is a sequence of workpiece states and the human response is a sequence of human action states that are likely responsible for the scenario. However, before the human action states can be extracted, it is necessary to pick the right HMM for the given task scenario that contain the human action states. Consider a task scenario represented by the workpiece observation sequence  $O_Q$  as

$O_Q = \{WP\_C\_T, WP\_C\_M, WP\_C\_B, WP\_R\_T, WP\_R\_MB, WP\_L\_T, WP\_L\_MB\}$ . The 'Forward' algorithm [19] is used to obtain the probabilities of observing  $O_Q$  given the two HMMs  $\lambda_{T1}$  and  $\lambda_{T2}$  as  $P(O_Q | \lambda_{T1}) = 8.34e-7$  and  $P(O_Q | \lambda_{T2}) = 3.12e-7$ . Since  $P(O_Q | \lambda_{T1}) = 8.34e-7$  is the highest probability,  $\lambda_{T1}$  is picked as the most likely model to represent the task scenario  $O_Q$ .

- Using the 'Viterbi' algorithm [19], HMM  $\lambda_{T1}$  is queried with the workpiece state sequence  $O_Q$  to obtain the most likely sequence of human action states  $H_Q$  that could produce the given task scenario as  $H_Q = \{H\_C\_T, H\_C\_M, H\_C\_B, H\_R\_T, H\_R\_MB, H\_L\_T, H\_L\_MB\}$

Similarly, multiple task scenarios can be queried from the HMMs to obtain the human actions responsible for them. Because of the stochastic nature of the HMMs, human response to not only captured task scenarios but also those that are not captured can be extracted. From these extracted human action states, the constituents of manufacturing knowledge are decoded.

Step 5) Decode: The main objective and innovation of this step is to decode four key manufacturing knowledge constituents of the



**Fig. 9.** Layup strategy adopted by the expert laminator.



composite layup task from the extracted human action states. The constituents are i) Task strategy, ii) ply manipulation techniques, iii) mechanics of the laminator's motion during task execution, and iv) problem solving approach used to correct layup errors.

- i. Task strategy: The approach taken by the technician to lay the ply on the mould depends on the geometry of the mould, the deformation characteristics of the ply and the awareness of sector dependencies where one sector must be laid before another to avoid layup errors. In this case, the task strategy can be observed from the sequence of actions taken by the technician to perform the task. This sequence is already obtained in the previous step where human action state sequences are obtained for any given task scenarios. For example, for task scenario  $O_Q$ , the human action sequence obtained was  $H_Q$  which when superimposed on the mould shows the task strategy adopted (Fig. 9).
- ii. Time taken: The time taken by the laminator to layup each sector of the workpiece can also be obtained from the human action states by using the capture timestamps stored. With this knowledge, workpiece areas that take longer to layup than others indicating higher layup complexities in those sectors, can be automatically identified (Table 5).
- iii. Precise human motion: The actual action data from within each extracted human action state is obtained from the

spreadsheet that contains the laminator's skeletal motion data. The x, y and z motion of the laminator's left and right hands are plotted against time so that the motion patterns can be visualised thereby revealing the ply manipulation techniques used in each state. As an example, the technician's hand motion during action state 5 ( $H_{C_B}$ ) is shown in Fig. 10. Similarly, motion charts of the rest of the upper body joints, such as head, neck, elbows, shoulders, and torso can also be plotted and visualised.

- iv. Ply manipulation techniques: According to the Elkington et al. [4], there are seven standard hand ply manipulation techniques. The techniques are (i) one handed guiding, (ii) two handed guiding, (iii) manual folding, (iv) mould interaction shearing, (v) double tension shearing, (vi) tension secured shearing, and (vii) smoothing and tensioning. One or more of these techniques are used within each of the human action states and therefore can be isolated and revealed as an important constituent of layup task knowledge. The laminator's hand motion charts during the techniques are listed in Fig. 11.
- v. Laminator's motion mechanics: The skeletal joint coordinates belonging to the laminator's upper body are recorded in the capture step of the framework. From these joint coordinates, several motion parameters can be obtained using vector computing. Examples of four different motion

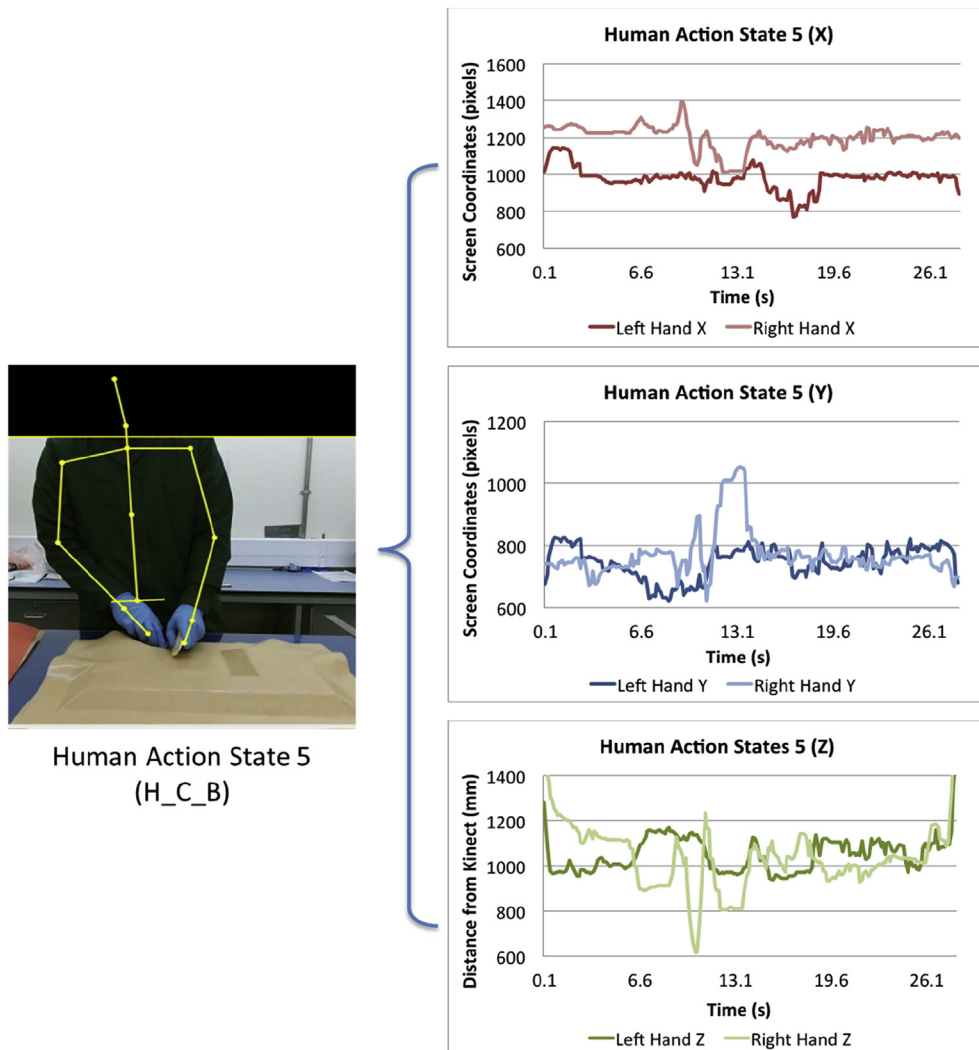


Fig. 10. Layup strategy adopted by the expert laminator.

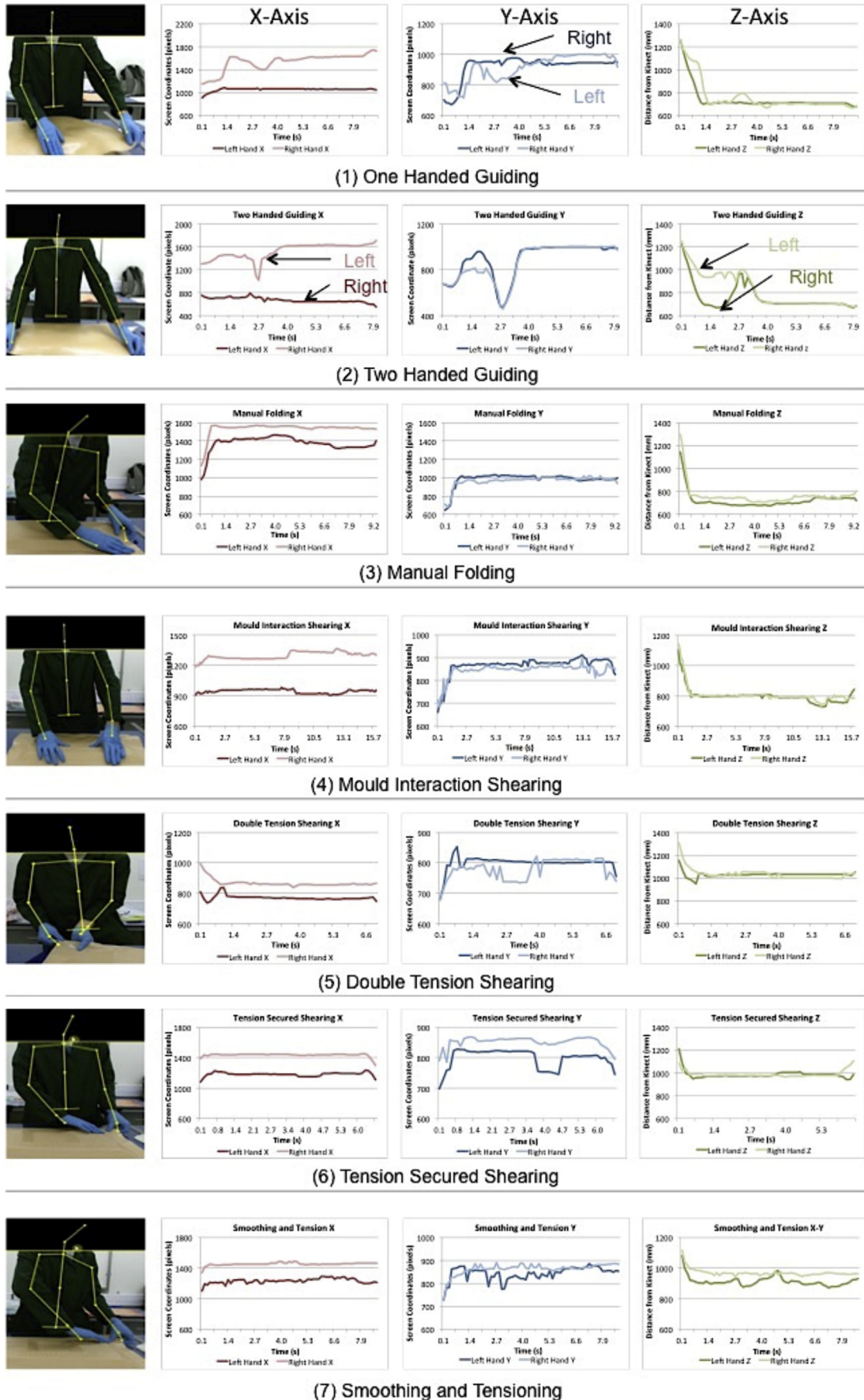


Fig. 11. Ply manipulation techniques used by the expert laminator.

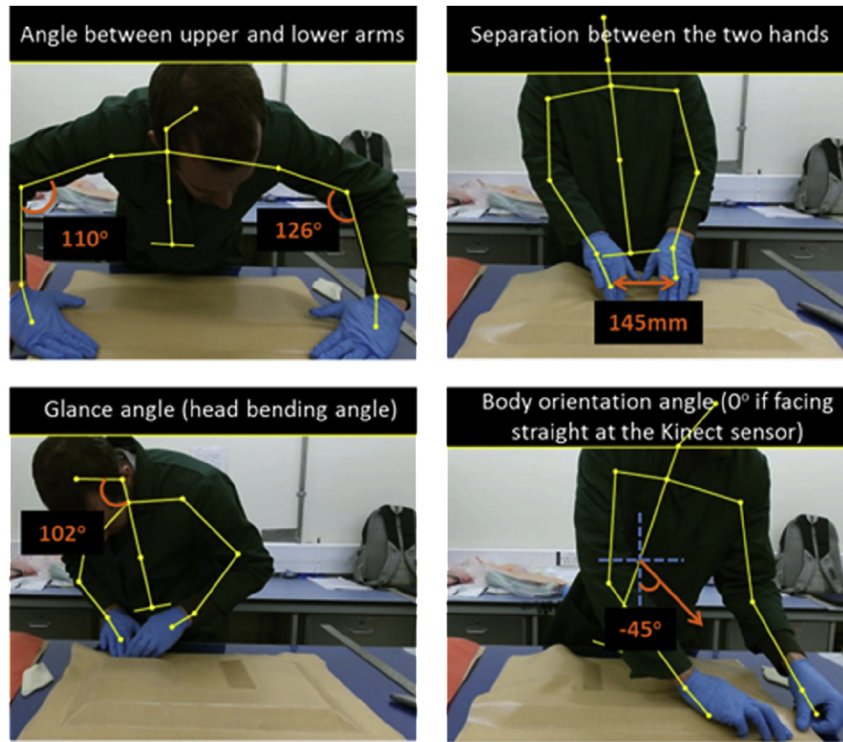


Fig. 12. Laminator's motion mechanics during the layup task.

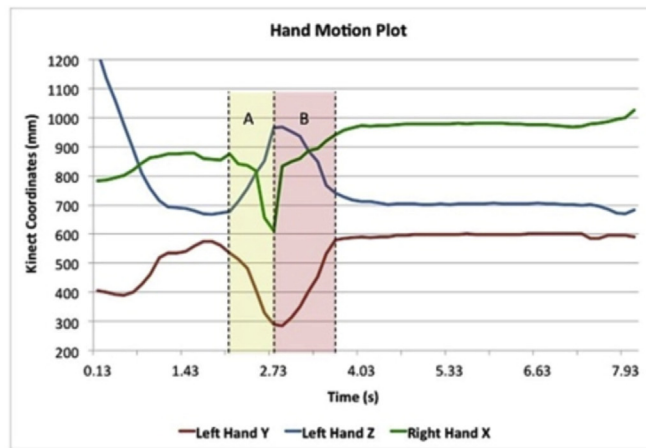


Fig. 13. Laminator's hand motion speeds during the layup task.

mechanics computed using skeletal coordinate data is shown in Fig. 12. This data helps in visualising the laminator's body posture and orientations, glance angles and the positions of his hands with respect to the ply and the mould while performing critical hand layup techniques.

Another influential constituent of motion mechanics that is critical to the success of the layup is the laminator's hand speed while performing ply manipulation [6]. A small portion of hand motion chart is shown in Fig. 13 and the hand speed in two zones A and B is computed from coordinate data stream of the hands. The screen coordinates are converted to real-world coordinates to obtain speed values in mm/s rather than in pixels/s.

vi. Laminator's problem-solving approach: In this study, the laminator deliberately introduced an error into the task. A

#### In zone A:

Right hand X speed = 228.6mm/s

Left Hand Y speed = 277.5mm/s

Left Hand Z speed = 440mm/s

#### In zone B:

Right hand X speed = 364.6mm/s

Left Hand Y speed = 377.7mm/s

Left Hand Z speed = 211mm/s

simulated error was made while laying up the ply on a particular area of the workpiece resulting in a wrinkle on the surface. If not resolved, the wrinkle might result in a serious surface defect that could weaken the structure post curing. The laminator using a 3-step approach removed the wrinkle from the surface of the ply. This problem solving scenario is represented by the workpiece observation sequence  $O_{QP}$  as  $O_{QP} = \{WP\_C\_M\_P, WP\_C\_M\_PS1, WP\_C\_M\_PS2, WP\_C\_M\_PS3, WP\_C\_M\}$

In order to understand this approach, the HMM that most likely represents this scenario is chosen using the 'Forward' algorithm. The chosen HMM is  $\lambda_{T2}$  from which the human action sequence  $H_{QP}$  that is most likely responsible for  $O_{QP}$  is extracted using the 'Viterbi' algorithm (Fig. 14).  $H_{QP} = \{H\_C\_M\_P, H\_C\_M\_PS1, H\_C\_M\_PS2, H\_C\_M\_PS3, H\_C\_M\}$



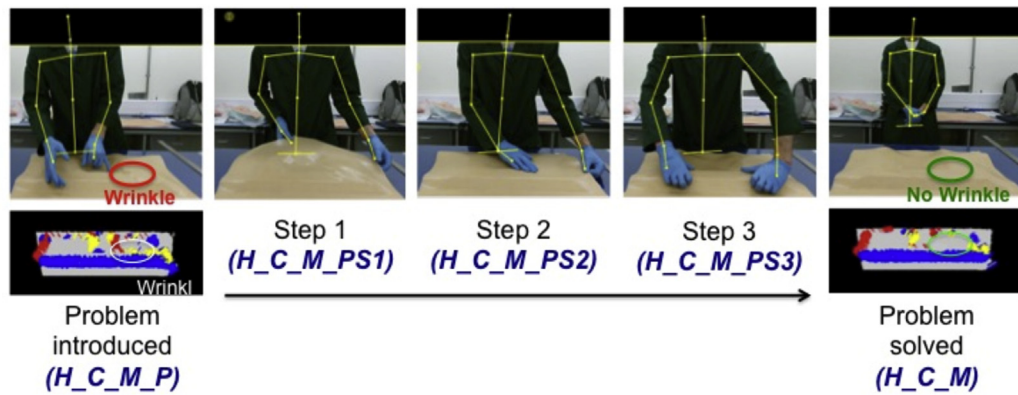


Fig. 14. Laminator's problem-solving approach during the layup task.

Step 6) Reproduce: The captured human action and workpiece data consists of a stream of skeletal joint coordinates of the technician's upper body and the progress of the workpiece as an accurate digital representation of the task. This way a task can be digitally captured and stored in a spreadsheet less than a megabyte in size instead of the usual practice of capturing and storing tasks in large video files. The skeletal coordinates stored in the spreadsheet can be rendered graphically to produce a stickman animation of the captured layup task (Fig. 15). However, when greater level of task detail, such as finger positions, is required then an animation does not suffice and the corresponding colour images can be referred to.

Though only 2D animation is used in this work, the digital nature of the extracted and decoded knowledge enables the 'Reproduce' step to also use graphics-rich media such as immersive virtual environments in which tasks can be demonstrated by virtual human avatars on virtual workpieces or the manufacturing knowledge can be augmented on a real environment during a task using mixed reality technologies. Both these methods help in enabling quick and cost-effective transfer of manual layup skills.

The two main innovations in this research work are: (i) the proposed human-workpiece interaction theory that for the first time seeks to integrate and expand Rasmussen's concept of skill-based, rule-based and knowledge-based behaviours, Rasmussen's concept of a decision ladder for problem solving and Gibson's theory of affordances during human-object interactions, in order to fully describe a manual skill-intensive task such as composite layup. The theory is then used to underpin the new digitisation

framework to extract manufacturing knowledge from manual tasks and (ii) the 6-step digitisation process that demonstrates the use of the theory and enables automated extraction and reproduction of manufacturing knowledge from skill-intensive manual tasks. The implementation of this process is demonstrated using low-cost gaming devices to simultaneously capture and digitise human actions and the more critically the effect of those actions on the deformable workpiece during a layup task. This is followed by using hidden Markov models to digitally represent and query the interactions between the laminator and the composite ply during the layup task. Interestingly, this research uses standard algorithms such as the 'Forward' algorithm, the 'Viterbi' algorithm and the 'Baum-Welch' algorithm to extract key knowledge constituents from the layup task, made possible because of the innovation in which the human-workpiece interactions are modelled within the hidden Markov model.

The significance of this research is its direct impact to facilitate quick and cost-effective skill transfer between people. The captured knowledge can also be used in a real-time supervision system using the Kinect sensor that watches the newly trained laminator do the task and benchmarks his/her layup actions against those captured and verified by the system. Any movements that are outside the acceptable limits are flagged as areas of improvements, thereby constantly refining the layup skills of new laminators. The proposed digitisation framework can also be an enabler for (i) automated analysis of manual tasks on the shopfloor to assess task ergonomics in real-time, (ii) real-time physical collaboration between remote

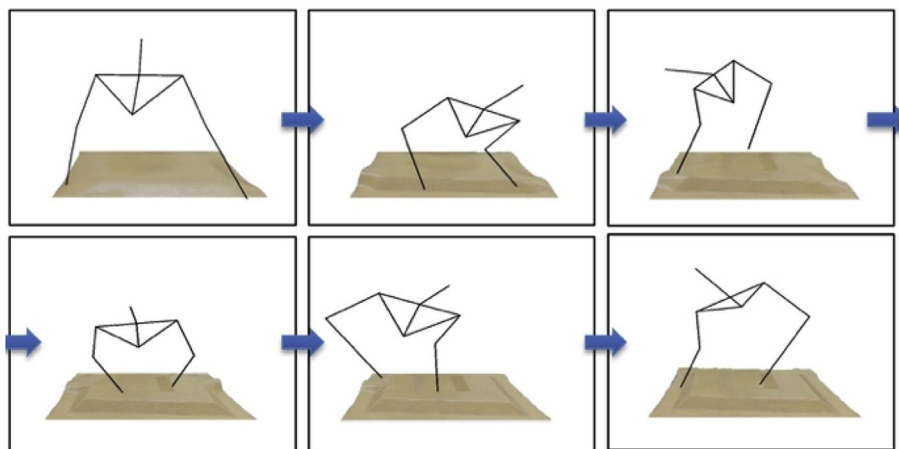


Fig. 15. Layup task animation which is a digital representation of the actual layup task as performed by the laminator.



engineering teams and (iii) intelligent automation of skill-intensive manual manufacturing tasks, all contributing towards enhancing the productivity of the manufacturing industry.

#### 4. Conclusion

The proposed digitisation process, underpinned by the human-workpiece interaction theory is successfully implemented for digitising the task knowledge embedded within a manual composite layup task. The framework itself is of a plug and play nature in which different methods, tools and techniques could be used in each of the 6 steps to implement it for digitisation of a variety of manual manufacturing tasks. In summary, this research contributes to knowledge in the five main areas, namely, (1) the theory of human-workpiece interactions to decipher human behaviour in manual manufacturing tasks, such as manual composite layup (2) a cohesive and holistic framework to digitise manual manufacturing task knowledge with well defined steps, (3) the use of low-cost gaming interface technology to simultaneously capture human actions and the effect of those actions on workpieces during a manual manufacturing task in an industrial setting, (4) a new approach to use hidden Markov models to represent human ability to perform a complex task on a workpiece and (5) extraction and decoding of manufacturing knowledge constituents from the hidden Markov models. The biggest contribution to research as a combination of all the above is the new ability to unearth and decode human skills that were always considered very difficult to extract and reproduce. In the future, more task observations need to be captured in order to extract layup knowledge from diverse task scenarios to increase the depth of this study. Involving multiple laminators with varying degrees of expertise would also provide a means to digitise each laminator's knowledge into distinct representations of individual skill models to be used in skill training and assessments.

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