1 Introduction

Human-controlled positioning systems are used throughout the world to perform challenging manipulation tasks. As these mechanical manipulators become more complex and powerful, it is crucial that the role of the human operator be streamlined, and that operators be adequately trained. Otherwise, human-machine interaction problems could have a significant negative influence on productivity, system reliability, and safety.

Auxiliary control schemes can be added to human-operated systems to improve performance. For example, even a skilled crane operator can have difficulty maneuvering a payload without inducing large amounts of sway. Therefore, a secondary control scheme may be added to ensure low-sway motions. However, these secondary control schemes must augment the operator’s intended commands. This has the potential of confusing or annoying an operator, possibly resulting in poorer overall performance. Therefore, it is necessary to understand the cognitive skills of operators and to study their decision-making processes [2]. Unfortunately, the nature of the human-machine interaction depends on each individual and the machine they are controlling. Therefore, for any given class of machinery, it is necessary to study numerous human operators.

The system studied here is the human-operated bridge crane sketched in Fig. 1. When a human operator attempts to maneuver payloads using an overhead bridge crane the oscillations make it difficult to manipulate the payload quickly and with good positioning accuracy. If the workspace is cluttered with obstacles, then the oscillations can create significant safety issues, especially when the payload or obstacles are of a hazardous or fragile nature. A typical bridge crane payload response is displayed in Fig. 2. The figure shows an actual payload trajectory as measured with an overhead vision system while an operator attempted to maneuver the payload to a desired target location. In this case, the operator collided the payload with two of the obstacles.

Input shaping has proven effective for controlling the oscillation of several types of cranes [3–10]. Input shaping is implemented in real time by convolving the human-generated command signal with an impulse sequence (an input shaper). This process is illustrated in Fig. 3 with an initial pulse input, \( p(t) \), and an input shaper containing two positive impulses. The result of the convolution is the input-shaped command, \( u(t) \). This shaped command is used to drive the system actuators. The key to designing an input shaper is knowledge of the system’s natural frequency, \( \omega \), and damping ratio, \( \zeta \). This information is used to calculate the amplitudes and time spacings of the impulses in the input shaper.

For example, the amplitudes and time locations of the impulses in the two-impulse shaper shown in Fig. 3 are [11,12]:

\[
\begin{bmatrix}
A_i \\
T_i
\end{bmatrix} = \begin{bmatrix}
1 & K \\
1 + K & 1 + K \\
0 & 0.5T_d
\end{bmatrix}, \quad i = 1, 2
\] (1)

where

\[
K = e^{-\frac{\zeta\pi}{1-\zeta^2}}
\] (2)

and \( T_d \) is the damped period of vibration. Note that the time of the first impulse in an input shaper is always set to zero. Furthermore, in the case of an undamped system such as a crane, the two impulses both have an amplitude of 0.5. This is the case shown schematically in Fig. 3.

The simple two-impulse shaper given in Eq. (1) is called a zero vibration shaper because it ensures zero vibration when the system model is perfect. However, when there is uncertainty in the oscillation frequency there may be significant residual oscillation. Therefore, it is also important to choose an input shaper that is suitably robust to the expected system parameter variations and modeling errors [11,13,14]. More robust input shapers will contain more impulses and will slightly increase the rise time. Two commonly used robust shapers are the zero vibration and derivative shaper given by [11]:

\[
\begin{bmatrix}
A_i \\
T_i
\end{bmatrix} = \begin{bmatrix}
1 & 2K \\
(1 + K)^2 & (1 + K)^2 \\
0 & 0.5T_d
\end{bmatrix}, \quad i = 1, 2, 3
\] (3)

and the extra-insensitive (EI) shaper for undamped systems given by [13,15]:

\[
\begin{bmatrix}
A_i \\
T_i
\end{bmatrix} = \begin{bmatrix}
1 & K^2 \\
(1 + K)^2 & (1 + K)^2 \\
0 & T_d
\end{bmatrix}, \quad i = 1, 2, 3
\] (4)
This research effort has addressed this problem. The first is by teaching models for courses around the world: new teaching methods and laboratory equipment have been developed at Georgia Tech. The goal is to increase the presence of input shaping in the engineering curriculum and create teaching models for courses around the world [16]. This paper will focus on the first task—observing crane operators.

Note that the input-shaping process lengthens the command by the duration of the input shaper, as was shown in Fig. 3. As a consequence, when the operator issues a “stop” command to the crane, the overhead support point will continue to move for a short period of time. At first, it may seem that this artifact would cause a compatibility problem with the crane operator. In fact, this issue is one of the primary motivating factors for this study.

Even without input shaping installed, crane payloads continue to move after the operator has commanded them to stop. The first cause of the continued motion is the large inertia of a crane. The motors and breaks simply cannot stop the crane bridge and trolley immediately. Furthermore, the payload will often continue moving until it swings out far enough that the suspension cables create a deceleration force. But, of course, the payload then starts to swing backwards and begins oscillating. As a result of these dynamic effects, crane operators become proficient at issuing stop commands well in advance of the intended location. The important question addressed here is whether or not the deceleration delay from input shaping is any more troubling than the natural deceleration delays that already exist in cranes. The data will show that crane operators appear to have very little problem handling the input-shaping deceleration delay.

This research was conducted using a 10-ton bridge crane at Georgia Tech. Numerous operators drove the crane through obstacle courses both with and without the input-shaping controller enabled. Data from these experiments were analyzed to determine how the payload trajectories varied and how the crane operators utilized input shaping. The experiments were comprised of three different studies. The first study simply observed operators driving a bridge crane both with and without input-shaping control. The time to complete manipulation tasks, the number of payload collisions, and the choice of trajectories were recorded. The second study tested a set of novice operators and observed their performance over a period of several weeks. This study investigated the operators’ ability to learn and gain skill. However, the testing frequency was fairly low; and therefore, significant learning did not occur. A third study used a diverse group of volunteers and tested them at a much higher frequency, so that measurable learning occurred.

The next section describes the 10-ton input-shaped bridge crane. Section 3 discusses the experimental results comparing unshaped and input-shaped crane operation. Sections 4 and 5 discuss the operator-learning studies. Conclusions are presented in the final section.

2 Input-Shaped Bridge Crane

The major components of the Georgia Tech crane are the bridge, the trolley, the payload, and the control system. The bridge is an I beam that moves forward and backward. The trolley moves left and right along the bridge. The hoisting mechanism, hoisting cable, and payload hang from the trolley. Its usable workspace is approximately 20 feet high, 30 feet wide and 140 feet long.

The crane has been used in a standard operating mode since 1992. In 2000, the crane was being used to move a sensitive piece of manufacturing equipment valued at over $600,000. During the move, the equipment shifted in the rigging and fell to the ground.

where \( V \) is a tolerable limit on vibration amplitude and \( T \) is the undamped period of vibration. The equations describing the EI shaper for damped systems are available in the above references. Innovation and experimentation alone may not increase the usage of input-shaping technology in the crane industry. Input shaping must also become a technique that is widely understood and recognized by engineers in the industry. In other words, lack of education is a significant impediment. There are two ways that this research effort has addressed this problem. The first is by focusing on how crane operators learn to use input shaping while manipulating payloads. The second is by focusing on teaching input shaping in the classroom. In the first case, the primary task is observing: studies are conducted to compare how well crane operators manipulate payloads with and without input shaping installed. The goal is to determine if input shaping is compatible with human operators and whether it makes crane operation safer, more efficient, and easier. In the second case, the primary task is teaching: new teaching methods and laboratory equipment have been developed at Georgia Tech. The goal is to increase the presence of input shaping in the engineering curriculum and create teaching models for courses around the world [16]. This paper will focus on the first task—observing crane operators.

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The crane has been used in a standard operating mode since 1992. In 2000, the crane was being used to move a sensitive piece of manufacturing equipment valued at over $600,000. During the move, the equipment shifted in the rigging and fell to the ground.
The machine was deemed a total loss. This motivated the upgrade
to an input-shaping crane controller. Some new hardware compo-
nents were added to the crane to implement input shaping. Figure
4 shows the configuration of the new hardware and how it gener-
ates the input-shaped control signal. Button signals generated by
the human operator travel from the control pendant to the hoist
controls and to the bridge-and-trolley control box. A Siemens
CPU314C-2DP programmable logic controller performs
the input-shaping algorithm. The resulting commands are then
sent to the trolley and/or bridge motor drives. These drives use the
incoming commands from the PLC as velocity set points for the
motors. To ensure accurate execution of the commands, the drives
are Siemens Masterdrives Series AC-AC inverters. This type of
drive uses a pulse-width-modulated signal to accurately control
the motors. Inverter duty capable motors were selected to ensure
good compatibility with the drives.

Figure 2 compares a typical input-shaped payload response to
the unshaped response discussed earlier. When input shaping is
enabled, the payload sway is virtually eliminated. The two cases
shown are from the same human operator. The only change was
that input shaping was enabled by turning a knob on the control
pendant.

To capture this data, a camera was mounted overhead and the
entire motion through the obstacle field was videotaped. An
image-processing algorithm in MATLAB was then used to extract
the payload motion. The target used to mark the payload was
optimized for this particular tracking algorithm [17]. The tracking
code is an adaptation of an algorithm originally designed for
tracking biomechanical motion, specifically that of pole vaulters
[18]. This original algorithm was based on techniques used to
accomplish motion estimation for frame prediction in camera
video sequences. More recently, the methods that inspired this
implementation have been adapted to perform in biomedical ap-
lications aimed at reconstructing magnetic resonance imaging
data sets [19].

This target-tracking algorithm relies primarily on the intensity
information that is provided by a video sequence. First, search
regions are defined by the code operator in the initial frames of a
video sequence to identify the crane payload in respective images.
Next, thresholding is applied in order to isolate a differentiable
region of the moving object. All pixels within the selected image
that occupy this region are used to determine the centroid of the
target. Based on the first- and second-order derivatives of motion,
the algorithm predicts the location of the target in the next frame
and the search region for that frame is centered around the pre-
diction. The thresholding operation is repeated for this next frame
and the location of the target is determined via the centroid cal-
culation.

Using this methodology, an entire video sequence can be
tracked automatically following the user input required for the
first few frames. Given that the centroid calculation is based on
intensity information, varying lighting conditions can be problem-
atic. In the event that lumination cannot be controlled, a dynamic
threshold value can be effective in maintaining accurate results.
Because manipulation of this threshold is allowed during an ex-
traction process, the tracking algorithm used here is able to per-
form with greater accuracy than some more complicated imple-
mentations based on block matching and optical flow.

3 Effects of Input Shaping on Performance

A crane operator must be careful to avoid damaging collisions
between the payload and obstacles. On the other hand, a crane
operator must work with a high level of speed and efficiency.
Therefore, a real crane operator must make difficult decisions on
how fast to go and what paths to take in a cluttered work envi-
ronment. Given that input shaping changes the dynamic nature of
the crane, it is important to investigate how operator performance
and behavior change with the addition of input shaping.

Volunteer operators ran the bridge crane through the obstacle
courses shown in Figs. 5 and 6. Each operator ran the crane both
with and without input shaping. The goal was to move the crane
from the start region to the end region quickly, but without run-
ning into any obstacles. In order to observe changes in operator
behavior, each course has distinct path choices for reaching the
target. These long and short paths are shown schematically in
Figs. 5 and 6. The shorter paths have more narrow bends and turns as compared to the longer paths. Therefore, they require comparatively more accurate positioning. A total of 23 volunteers drove the crane through these obstacle courses. Ten operators were tested on Course 1 and 13 operators on Course 2.

3.1 Run Times. The amount of time required to drive the crane from the start region to the end region was recorded. Figures 7 and 8 show the run times for Courses 1 and 2, respectively. The dark bars represent the unshaped runs, whereas the light bars represent the runs with input shaping enabled. The end time was defined as the moment at which the payload entered the target zone and did not subsequently swing outside the zone. The target area was a 22-in.-diameter circle. The average times to complete the courses with input shaping were 31 s for Course 1 and 51 s for Course 2. On the other hand, the average times for the unshaped runs were 88 and 135 s, respectively. In other words, input shaping improved the completion time by 284% on Course 1 and 265% on Course 2.

Note that the definition of the completion time given above was usually advantageous to the unshaped trials. The residual payload oscillation without input shaping was often a foot or more in amplitude when the end time was recorded. On the other hand, there was virtually no residual vibration when input shaping was utilized. Therefore, if a more demanding completion requirement had been specified, i.e., a smaller target zone, then the unshaped task completion times would have been much larger, whereas the shaped tests would have been virtually unchanged. In any case, the data clearly indicate that the crane operators took much less time to perform their manipulation tasks when input shaping was enabled.

The volunteers had a variety of crane operating experience. Some were regular users of the crane, while others had only driven the crane a few times when they were asked to participate in this study. The institutional review board protocol approved for this human subject testing did not allow us to associate individual operators with their performance. Therefore, we cannot segregate the data into skilled and unskilled operator subsets. However, visual observation of the tests indicated that even skilled operators had difficulty navigating the courses when input shaping was disabled. The few cases where the unshaped performance was close to the shaped performance appeared to occur more from random luck, rather than from highly skilled manipulation.

3.2 Choice Between Long or Short Route. Input shaping effectively reduces the dynamic complexity of the crane. Thus, operators tended to be more aggressive and took the shorter and more efficient, but also more challenging, routes when input shaping was enabled. Hence, the choice of a shorter path and an improvement in crane control combined to yield the much shorter run times shown above. Figures 9 and 10 compare the number of people that took the short and long routes for both obstacle courses. For Course 1, all ten operators chose the short path for their shaped run, whereas for Course 2, 11 out of the 13 crane operators chose the shorter route for their shaped run. Without input shaping, the majority of operators took the longer, but simpler, route through the obstacles. This indicates that, with input shaping enabled, the crane operators felt more confident and chose the shorter route despite its complexity.

Note that navigation through the obstacle courses did not involve hoisting of the payload. Although hoisting is a common crane operation, this study focused on two-dimensional manipulation tasks. Previous studies with cranes undergoing hoisting have shown that input shaping is very effective in many cases [8].
4 Operator Learning Experiments

Although input shaping cancels out payload swing, skilled operators can also employ manual swing control techniques to reduce payload sway. On the other hand, most novice crane operators rely on a passive approach for swing cancellation. They limit themselves to slow and simple movements in an attempt to avoid large oscillations. When large oscillations do arise, the operators usually have to take less challenging paths to the target, or they make numerous small motions to proceed slowly through a dangerous region. This tactic works, but results in long task completion times.

To achieve shorter times, it is necessary to move at maximum velocity most of the time, which can cause a large swing. It turns out that large swings can be actively damped by appropriately manipulating the horizontal force. Unfortunately, a badly timed active control can amplify the swing. Acquiring the skill to achieve an effective manual swing control thus requires a fair amount of practice.

The learning patterns of human operators can be quite sophisticated. If the control task is repetitive, some knowledge can be extracted and patterns in the operator learning can be observed. Experiments have been done to study human capability to perform tasks by learning iteratively. Results from these experiments demonstrate the ability of human operators to perform the tracking of a desired trajectory for some unknown nonlinear system with quite reasonable accuracy during the iteration process.

It is a common observation that learning to perform a task often becomes easier after each attempt to perform the task. In order to investigate this phenomenon with bridge crane operators, student volunteers were asked to drive the crane through the same obstacle course several times over a period of ten weeks. Twelve volunteers drove the bridge crane through the obstacle course shown in Fig. 11. A single trial consisted of both an unshaped run and a shaped run. Each operator drove the crane between three and seven different times. The average number of trials per operator was 4.5. The average testing frequency for all of the operators was 0.6 trials/week. This testing frequency was fairly low, so the question arises as to whether or not a subject learned from one test to the next. As it turns out, the data show that the operators did not appear to develop any significant crane operating skill.

4.1 Run Times. Figure 12 shows the progression of completion times without input shaping for all of the subjects. If the operators were learning to run the crane more effectively, then there should be a downward trend in completion time as the number of trials increases. However, there is no such trend to indicate that the operators were learning. Figure 13 shows the corresponding information when input shaping was enabled. Once again, operator learning appears to be absent. Nevertheless, the completion times with input shaping are considerably faster than without shaping. In fact, many of the runs are near the theoretical minimum move time that is set by the velocity limit of the crane. To clearly show the absence of learning, Fig. 14 plots the average time to completion for the unshaped and shaped runs over the first five trials. The volunteers were able to consistently perform their task more quickly with input shaping than with no vibration control. However, no improvement occurs with increasing trials.

4.2 Collisions. The ability of the operators to navigate the experimental course without collisions was closely monitored. Figure 15 shows the total number of collisions from the shaped and unshaped experiments. Again, the data do not indicate a significant learning effect; the incidence of collisions shows only a slight downward trend. However, the use of input shaping nearly eliminated collisions, even in the first trials.

4.3 Choice of Route. There are both long and short paths to the goal location, as shown in Fig. 11. Once again, the short route
was intentionally made more difficult. Figure 16 compares the number of operators that chose the long and the short routes. For the shaped runs, more people chose to take the shorter route. This trend was reversed for the unshaped runs. In the shaped cases, 46% of the total runs were made through the long route, whereas in the unshaped cases, 77% of the total runs were made through the long route.

5 High Frequency Operator Learning

The frequency of testing the operators was rather low for the study described above. There were gaps of 1–3 weeks between each test. If the time gap between tests is too long, then the learning effect will be small, as was clearly demonstrated by the data. To test the effect of increased training frequency, another group of volunteers was recruited for an additional study. The average testing frequency was 2.2 trials/week. This testing frequency was nearly four times higher than in the first study. Some operators drove the crane only three times, whereas others drove the crane up to nine different times. The obstacle course was changed somewhat to diversify the data set. The resulting configuration is shown in Fig. 17.

Figure 18 shows the task completion time for a typical subject. After only a few trials, the operator became more skilled at running the crane without input shaping. On the other hand, the operator learning did not help much in the cases when input shaping was enabled. Even though the operator became more skilled over time, the performance without input shaping was still considerably poorer than when input shaping was utilized. Figure 19 shows the progression of completion times without input shaping for all of the operators. There is a clear downward trend in completion time as the number of trials increases. Figure 20 shows the corresponding information when input shaping was enabled. In this case, the operator learning does not have a big effect on task completion time. However, the completion times with shaping are considerably faster than without input shaping, even after substantial operator learning on the unshaped crane. The results from both learning studies indicate that significant learning is not needed when input shaping is utilized. With input shaping enabled, crane operators immediately become safer and more efficient in their manipulation tasks.

6 Conclusions

The actions of numerous bridge crane operators were videotaped and the change in their performance and behavior while using input shaping was recorded. The results indicate that operators can move through obstacle fields much more quickly when input shaping is utilized. Furthermore, the operators have greater confidence in their maneuvering capabilities. It was observed that crane operators took more complex, but more efficient, maneuver-
input shaping was not used, operator learning helped improve the crane performance. However, the data indicate that input shaping plays a bigger role in improving performance than learning. Novice operators using input shaping can perform better than moderately skilled operators who do not have the aid of input shaping.

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References