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Virtual Welding – A Low Cost Virtual Reality Welder Training System Phase II

Final Report

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Executive Summary

The goal of this project was to develop a realistic, low-cost welding training system based on virtual reality technology. Welding is a key skill for shipbuilding and welding training is a significant expense for shipbuilders. Improvements in the training process and any reduction in the time required to train and qualify welders will provide a cost benefit to the shipbuilding industry.

Low-cost was seen as a critical issue for this project. There are other commercially available virtual welding systems on the market already. However, due to their high initial cost none have been purchased by any of the commercial shipyards in the U.S. The goal of this project was to create a system that could become a successful commercial product at a significantly lower cost than other available systems. The means to achieving a low-cost system was to make use of consumer level equipment and to repurpose existing weld monitoring software for use in weld simulation.

A working virtual welding system has been developed. It consists of a typical GMAW welding torch, a modified welding helmet containing a small video display, and a typical suitcase wirefeed controller. The motion of the torch is tracked using a commercial video tracking system. Users can make virtual "T" fillet welds on a test plate. The welds are simulated using specialized neural network software derived from a commercial weld monitoring system. The resulting welds can be reviewed and analyzed for weld quality and external and internal weld shape.

Multiple prototype units have been built using the final design developed under this project. These units have been deployed to shipyard welding schools and other welding training schools. User and instructor feedback on the use of the virtual welder system was collected at each site.

The weld simulation algorithm is known to produce very accurate results for the specific measured input from the user. However, user feedback indicates the system does not give the same impression as real welding. Additional work will be required to improve the realistic welding feel of the system.

The primary technology developer, Native American Technologies, intends to continue development of the current system. The goal is to create a sustainable commercial product.

A usable low-cost virtual welding system has been created for use in welding training. The current prototype version represents a baseline for functionality and design, serving as a proof of concept. It is expected that the current design will be further developed and enhanced into a marketable commercial product. We believe that if a low-cost virtual welder product were available that it would find an eager market among equipment manufacturers, trade schools, and technical colleges, in addition to the initial focus of shipyards and the shipbuilding community.

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Project Overview

The goal of this project was to develop a realistic, low-cost welding training system based on virtual reality technology. Welding is a key skill for shipbuilding and welding training is a significant expense for shipbuilders. Improvements in the training process and any reduction in the time required to train and qualify welders will provide a cost benefit to the shipbuilding industry.

In 1995, after viewing a neural network weld process model embedded into a real-time weld monitoring system called ArcSentryTM, developed by Native American Technologies (NA Tech), Mr. Howard Cary, Vice President of Hobart Brothers Company, worked with NA Tech to create a Virtual Reality Welder Training System for the Hobart Welding School. The ArcSentry System used an artificial neural network to produce a highly accurate 2-dimensional cross section of a weld by taking real-time data from robotic welding systems. A 3-dimensional virtual reality image was created from the 2-D information produced as the weld progressed. The ArcSentry Virtual Reality weld monitoring system is used in manufacturing systems to monitor robotic and automated welding processes.

The ArcSentry software was utilized to create a virtual reality 3-dimensional image for the Hobart welder training system. NA Tech was working closely with Texas Instruments, which had developed a high resolution color digital camera, which was used to track the motion of the manual welding torch. However, a short time into the development project, Hobart Brothers Company was acquired by Illinois Tool Works. This corporate acquisition halted the project. NA Tech proposed to continue the work on development of a Virtual Reality Welder Training System to the Navy SBIR Program, however, that proposal was not funded, and the Virtual Reality Welder Training System was temporarily shelved by NA Tech.

The initial idea of a virtual reality welding system for the shipbuilding industry was proposed in 2002 by John Holmander, then Site Manager of Electric Boat Quonset Point (Quonset Pt, RI). The potential benefit of such a system was recognized by the shipbuilding community. A series of Navy ManTech projects funded the development of a practical virtual welding system over the next four years. Since that time a number of other systems have been developed. Most of the systems remain experimental but one system, the end result of the earlier ManTech work, has become a commercial product with some market success.

The intent of this current project was to develop a new virtual welder based on the original ArcSentry software and Hobart Virtual Reality Welder Training System that also that took advantage of advances in consumer electronics and simulation software. The goal was to create a system that could become a successful commercial product at a significantly lower cost than other available systems. Low-cost was seen as a critical issue because none of the private shipbuilders had been able to afford the purchase of one of the currently available virtual welding systems.

The initial scope of this project was to provide a simulation of single pass GMAW (Gas Metal Arc Welding, also known as MIG, Metal Inert Gas) welding. The target weld specification was for at "T" fillet on 3/16" steel plate in the horizontal position. This was aimed at mid-tier commercial shipbuilding. As time allowed, the types of welds to be simulated would be expanded.

This project was begun in 2008 under the management of Bender Shipbuilding and Repair. The major technology provider was Native American Technologies (Golden, CO). Other participants included Electric Boat Corporation (Groton, CT), and Bollinger Shipbuilding (Lockport, LA). This project has been associated with a number of different NSRP Panels. It was sometimes listed under the Crosscut Panel (Workforce Development Panel) due to the emphasis on training. The Program Technical Representative (PTR) was from the Welding Panel. The majority of NSRP status reports have been given through the Production Process Panel (Planning, Production Process & Facilities Panel).

The original project was planned as a two-year, two-phase project with a go/no-go decision gate at the completion of phase 1. Around the time that phase 1 was completed Bender Shipbuilding entered financial difficulties. Although phase 1 was considered technically successful the work on phase 2 was not begun. After a year hiatus the project was restarted in 2010 under the management of Electric Boat Corporation (EB). Native American Technologies (NA Tech) continued to provide the primary technical input. Phase 2 was completed and the project closed out in February, 2012.



Figure 1. Full virtual welding system

The work completed under phase 1 included the development of a basic system design and the first iteration of hardware and software implementations. The first system made use of consumer gaming Wii remote devices for tracking. The virtual environment from the ArcSentry system was modified to include the display of the welding process, torch, arc, and resulting weld bead.

The ArcSentry software was modified to enable forward simulation of weld quality and shape based on virtual input instead of monitoring of actual welds from measured data. The ArcSentry software used a specialized neural network to calculate accurate weld results in real-time from a wide range of measured input values. At the end of phase 1 a rough prototype was demonstrated that could simulate the basic welding process.

This report covers work completed under phase 2 of the project, from February 2010 through February 2012. The current project used the same Statement of Work from the original proposal and mostly followed the same plan of development activities. The details of work done in phase 2 are presented in the following section. Deviations from the original plan are explained in the text. The Technical Approach section gives a roughly chronological account of the tasks accomplished in phase 2. The section subheadings correspond with the task breakdown in the original statement of work.

Phase 2 included the development of a final working virtual welder system and all of the software required to use the system as a welding training tool. The final system can be seen in Figure 1. The system uses a true to life welding torch, helmet, and controls, and simulates an accurate and realistic visual and auditory welding experience.

Technical Approach

Tracking

One of the activities done as part of phase 2 of this project was the conversion of the tracking system from consumer Wii remotes to a commercial camera-based sensor system. The tracking system was work that was intended to be completed under phase 1 of the project. The Wii remotes were demonstrated to work successfully in a lab environment. However, they used the Bluetooth protocol for wireless data communications and were prone to interference from cell phone headsets and other Bluetooth devices in real-world settings. The decision was made to switch to wired Infrared (IR) cameras for the tracking system.

The next iteration of the tracking system was developed using low-cost generic wired USB cameras with IR-pass filters. The wired cameras were only slightly more expensive than the Wii remotes. However, a significant effort was required to rewrite the tracking software to accommodate the change from Wii remotes to wired cameras. The Wii remotes did on-board processing to locate and isolate the tracked points and to identify multiple points as they moved over time. This functionality had to be replicated in our software. After much effort we were still not successful in developing a robust tracking system that could handle both the torch and helmet motions.

A decision was made to purchase and license a commercial tracking system. Even low-cost commercial tracking systems were quite a bit more expensive than using simple USB cameras. The advantage was that the provided tracking software was more reliable. Several types of cameras were examined and a small number of potential vendors were identified. Cameras from each of these vendors were obtained, and tested. Several visual tests were performed, as well as the work necessary to modify the existing software to process data from each camera system. As a result of this evaluation the choice was made to use OptiTrack V120:SLIM cameras from NaturalPoint (www.naturalpoint.com).



Figure 2. Early prototype system



Figure 3. Tracking camera detail

A set of OptiTrack cameras was purchased. The cameras came with software tools and a development environment for creating and integrating tracking into larger software projects. The new tracking system was integrated into the virtual welder system and made to work successfully. The tracking system made use of four cameras mounted on arms extending out from a central tower. This arrangement is shown in Figure 2. Over time it was noted that there were problems with the system losing its calibration. It was thought that the problem was associated with the cameras being moved. The cameras were mounted to the arms with adjustable fixtures that were locked into position with set screws. The camera mounting detail is shown in Figure 3.

In an effort to eliminate calibration problems and to make the system as robust as possible a newly available tracking system from NaturalPoint was tested. This consisted of three cameras permanently mounted inside of a stiff hollow bar, shown in Figure 4. The tracking bar was a slightly more expensive option than using the four separate cameras, but it proved to be very stable over time. The tracking bar was chosen for use in the final design.



Figure 4. Tracking bar

Helmet display

An effort was made to improve the helmet display system for the virtual welder. In the early prototype from phase 1 the display consisted of relatively low resolution video goggles. These goggles were put on first before the welding helmet. The helmet was a lightweight large-lens helmet with an opaque black lens to block any incoming light. The video display was somewhat difficult to put on and take off and it provided the minimum acceptable resolution. It was thought that there might be other alternatives for a higher resolution display that were still reasonably inexpensive.

This project worked with EB to help sponsor a Senior Capstone Project at the University of Rhode Island (URI) to research low cost display alternatives. Four seniors, two from Biomedical Engineering, one from Electrical Engineering, and one from Computer Engineering spent two semesters investigating low-cost, lightweight display alternatives and building prototype helmet displays.

Video goggles and virtual reality head mounted displays (HMDs) were found to fall into two broadly separated categories of consumer devices and commercial devices. The consumer devices were intended for use with mobile media players (i.e. Ipod) and were relatively low cost (\$200 - \$300). These consumer devices had a maximum resolution of 800 x 600 pixels and were more typically 640 x 480 pixels, or roughly standard definition (old) TV equivalent. Commercial devices were available with resolutions from 1024 x 768 through full HDTV (1920 x 1080) and beyond. The lowest cost commercial devices were about \$1500. The prices for the highest resolution models were more than 10 times that amount.

The URI students came up with some novel single-panel LCD display concepts where the helmet lens was replaced with a small inward facing LCD screen. One of these designs was tested at NA Tech, and though useful, was not suitable for production. In the end it was determined that there were no other alternatives than the known low-cost consumer products or the relatively high-cost commercial ones.

Capture of real welding experimental data

A neural network was used as the basis for the welding simulation program. In order to predict resulting welds from arbitrary input values the neural network was loaded, or "seeded" with a range of specific input data. The input data consisted of measured weld cross sections from a series of welds made with pre-determined parameters of current, voltage, wire feed speed, torch angles, etc. The specific range of input welds was established in phase 1 using a design of experiments analysis. A total of 89 welds were required to fully load the neural network.

Under this phase 2 project all of the experimental data welds were made. The welds were made using a fully automated multi-axis robot. This enabled the parameters for each weld to be changed in a random sequence without any manual setup of the welder. All of the weld samples used the same source materials. Two pieces of 3/16" x 2" x 6" A36 steel bar stock were joined with a "T" fillet weld in the horizontal position. Different weld parameters were used for each leg of the "T" so that each welded piece became two different specimens when it was complete.

After the samples were welded they were cut and polished and each weld cross section was precisely measured and recorded. Weld measurement was done using the NAMeS software from NA Tech. The final data for each weld – the input parameters and the cross section measurements - was then entered into the neural network.

Final prototype development

One of the major activities of phase 2 was the refinement of the hardware and software design of the final virtual welder system. Essentially every aspect of the system was modified from the early prototype developed under phase 1. This included the tracking system, the torch and helmet, the integrated tower and platform base, the controller electronics, the suitcase enclosure, the simulation and display software, and the Teacher Information System. Details of all these development activities are presented in the Results section of this report.

Field testing of prototype units

The original work plan envisioned a mobile trailer that would be outfitted with multiple prototype units and transported from location to location in order to provide testing opportunities. This plan was modified, and instead individual prototype units were delivered to a number of different locations and left there for an extended period of time for testing. Locations included welding schools at private shipyards, public Navy shipyards, and vocational welding schools. Evaluation forms were collected from the users at each testing location. In addition, detailed feedback was collected from the welding instructors. Early feedback was incorporated as changes to the later prototypes that were still being built. Later feedback was combined into lessons learned that will be used for future changes.

Upgrade plans

Early in the project the details of the system hardware were undergoing small but frequent changes. Toward the end of the project the hardware design began to stabilize. The final prototype system has proven to be fairly robust and the hardware design is unlikely to change for the time being. On the software side changes continue to be made to make the system more usable. In order to support the prototype systems that have already been delivered NA Tech has developed a plan for sending out automatic updates by CD. The CDs will load all of the updated software for each system, allowing them to be fully functional over a longer period of time.

Commercialization plans

NA Tech intends to continue development of the virtual welder and to create a fully supported commercial product. NA Tech has had preliminary discussions with a large welding equipment supplier relative to licensing agreements and expanded product development opportunities. An initial plan has been drafted which lays out the basic business model and costs associated with the virtual welder as a marketable product. The long term goal is to provide a low cost virtual welding system for sale back into the shipbuilding community.

Results

Welding experimental data

In order to collect data to load the neural network a series of real welds were made and measured. The experimental design for the 3/16" plate thickness "T" fillet joint called for 89 welds. Some additional samples were made by randomly selecting a few welds to be duplicated. This provided some statistical information about the data, which was used in training the neural network. In total over 100 welds were made and processed as sample data.

The sample welds that were made used different combinations of the 7 user-controllable input parameters listed in Table 1. The values for each parameter were set to discrete points within the allowable range given in the specification and outside of the allowable range. This provided for accurate simulation of both good welds and bad welds. The weld procedure was developed in phase 1 of the project. The specific weld chosen was thought to be typical of smaller commercial shipbuilding and applicable to newer lightweight naval designs.

Parameter	Range	Units
CTWD	0.5 - 1.0	inch
Offset	-0.1 -+0.1	inch
Travel Angle	0.0 - 15.0	degrees
Work Angle	40 - 50	degrees
Travel Speed	14 - 18	IPM
Voltage	28 - 31	volts
Wire Feed Speed	390 - 630	IPM

Table 1.	Welding	procedure	specifications
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The sample specimens consisted of a "T" fillet weld using 3/16" x 2" bar stock cut in 6" lengths. Different weld parameters are used for each leg of the "T". In this way each welded piece became two different specimens when it was complete. Welding was done using a multi-axis robot in order to precisely control the welding parameters. The welding setup is shown below in Figure 6.

The goal of the measurement process is to capture the dimensions of the resulting weld bead. In order to measure the penetration of the weld below the surface of the base metal and to see the shape of the inside of the weld the sample piece must be cut through to create a cross section. An example of the results of the sample preparation process is shown in Figure 5.

Low Cost Virtual Reality Welder Training System



Figure 5. Cross section sample

Each sample piece was carefully cleaned before welding to insure that no contamination was present on the samples, which could cause the welding process to be affected. First, the metal plates were thoroughly grit blasted. Then each plate was washed to remove any chemical contamination. Finally, just before welding, each sample was cleaned with ethanol and then rinsed and dried, and only handled with clean latex gloves prior to welding. The blasting machine is shown in Figure 7.



Figure 6. Articulated welding robot



Figure 7. Sample grit blasting machine

During welding real-time data was collected at a sampling rate of 20,000 data points per second (20 kHz). Data was collected using the NA Tech ArcSentry weld monitoring system, which was designed to collect data at up to 100 kHz. Most of the commercial weld monitoring systems operate at a maximum data rate of only 5 kHz, which makes them inadequate to diagnose many welding problems, and also incapable of collecting data which can be used to measure the energy bursts that create the welding sound. The human hearing range goes up to 20 kHz and this data collection rate enabled useful capture of data for sound simulation. Low frequency data from the weld (less than 10 kHz) is generally not seriously affected by contamination on the weld. For high frequency sampling it was extremely important to insure that the data was not altered by arc

plasma disturbances caused by contamination, and that the welding samples were completely clean and free of any contamination.

After the "T" was welded each weld was labeled and the specimen was cut, ground, polished, etched, and measured. Each individual step in this process was very important, and if not carried out with care it could result in data errors which would affect the database used for the neural network model. Heat from a cutting system can distort the shape of the weld in the final etched sample, because it is heat induced metallurgical changes in the metal that are viewed by the etching process. A cold cutting process was very important in order to obtain undistorted data. The data for some other welding simulator systems was developed without the proper care of the etched samples. Cooled saws can be used, but they tend to create saw marks which take more time to remove in order to get a clear enough image to precision measure the weld shape. A water cooled cut-off abrasive system was used here, which produces samples that are easier to grind, polish, and etch. However, in order to prevent heat damage to the sample, the standard coolant system did not provide sufficient cooling. An auxiliary cooling system and a very slow cut were used to prevent heat damage to the weld samples. The modified cooling system on the abrasive cutter is shown in Figure 8.



Figure 8. Abrasive cutoff wheel with auxiliary cooling system



Figure 9. Large heavy grinding system for sample preparation

The grinding step for a weld sample was important for getting a precise measurement. Full cooling was important, and slow and careful grinding was used. The approach used in most weld labs is to grind the sample as quickly as possible. This is an adequate method to produce samples for human viewing. However, for precise computer-based measurement of the weld size and shape proper grinding technique must be used. Fast grinding, as with fast cutting, causes distortion due to surface and sub-surface metallurgical reactions to the heat produced during the grinding process. Other welding simulation systems have utilized standard weld lab practice to grind samples. NA Tech used an old, heavy grinder, which provided a very stable grinding platform. This ensured that the measurement was not distorted by out-of-perpendicularity of the cross section surface that might occur with a less stable grinding system. The grinding system is shown in Figure 9.

In order to achieve the best definition of the weld shape in the final image the cut surface is polished. The step of polishing of the sample must be done with great precision. Often the polishing step is skipped in welding lab cross-section sample preparation. However, to obtain a high precision measurement, care must be exercised in sample polishing. In order to obtain a precision polished surface, a diamond polishing wheel system must be used. The polishing system used by this project is shown in Figure 10. If the sample gets hot during the polishing process the grinding media can "smear" the surface of the sample. This will distort the microscale heat-generated surface material and result in a distorted image.



Figure 10. Diamond wheel polisher



Figure 11. Chemical etching station

The final step in preparing the weld samples is chemical etching of the polished surface. Etching improves the contrast between the base metal, weld metal, and heat effected zone in the area of he weld. Simple etchants, typical of a welding lab, produce an image that is easily viewed by a human observer. However, when magnified by a microscope, the image will be blurred and an imprecise measurement will be produced. More complex mixtures of various chemicals must be used to obtain a very clear image so that a precise measurement can be generated for the neural network weld database. The etching station used in this effort is shown in Figure 11.



Figure 12. Measurement of weld cross section

Measurement of the weld shape was accomplished using a special version of the NA Tech NAMeS weld measurement software. Unlike the commercial version of the NAMeS software, this version was created to generate the measurement output in a system which digitizes the weld shape using a complex set of several hundred parameters. By using this software, which is proprietary and only used by NA Tech internally, a very precise weld shape can be reproduced in the graphics of the Virtual Welder System. An example of the detailed measurement that is possible is shown in Figure 12.

Each weld sample for this project was processed through the multi-step process described above. The resulting weld geometry measurement data was entered into a database along with the parameters used for each weld. When all of this data was complete it was loaded into the neural network.

The Neural Network Model

Weld Bead Shape

There is a growing interest in simulation programs that can predict the detailed geometry of the weld bead. Geometric data defining the shape of the bead can be used for assessment of weld quality. If such programs are sufficiently accurate, they can be applied as a tool in welding procedure development, welding simulation, and Virtual Reality. Different techniques based on both empirical modelling techniques and physical principles have been used for describing the weld bead shape or associated bead parameters. It should be noted that most of the references cited in this subsection deal with studies of steel weldments, but the principles discussed are also applicable in welding of aluminium.

Linear and non-linear regression techniques have been used for modelling the relationship between welding parameters and geometric data for description of the bead [1, 2]. As opposed to these traditional regression type models, neural networks have also been used for prediction of the whole weld bead [4, 5]. When neural networks are used weld geometry and engineering parameters can be derived with basis in the predicted whole bead shape. It has been shown that this approach yields a much more accurate prediction since many of the geometry parameters are not continuous as the weld shape varies, but the bead shape varies in a "smooth" way as the welding parameters are varied [6]. The neural network used here is a non-linear empirical model capable of sufficient multi-dimensionality to describe the entire weld bead shape.

Physical modelling techniques have also been used for modelling the shape of the weld bead. The mechanisms that determine the weld pool shape are very complex and include fluid flow, droplet detachment and metal transfer phenomena. For the majority of cases, the Peclet number is high enough to introduce significant effect from the convective heat transfer on the weld pool shape [7]. The driving forces for convection in the weld pool depend on the kind of heat source used. In arc welding, electromagnetic forces will contribute to the weld pool circulation, but in laser driven welds such forces are absent. In arc welds forces due to the surface tension temperature gradient (Marangoni effect), the buoyancy force, the electromagnetic body (Lorenz) force, and aerodynamic drag forces contribute to the convective flow in the pool [8, 9, 10, 11]. Models of this kind are frequently based on finite volume and finite difference techniques, but finite element approaches are also applied in modelling of weld pool convection.

Finite element models have been extensively used for prediction of residual stresses in welds. Details of the weld may have impact on the residual stresses in regions close to the weld but are not critical for proper prediction of the residual stresses in the heat affected zone. In such models, the approximate shape of the weld is implemented by using an appropriate heat source model to account for the heat power distribution in the weld pool [12]. In an even simpler approach, analytical models with distributions of elementary point heat sources and the method of images have been used for a qualitative prediction of weld bead shape [13].

Even though physically based models have become increasingly sophisticated and can account for several of the mechanisms that influence weld shape, they are still not useful for Virtual Reality applications since they usually require many hours to run, which is far too slow. If experimental data for weld shape are available, neural networks offer an alternative method for modelling the weld shape since these models are capable of capturing all of the complexity of the welding process. Such empirically based models represent a completely different approach to weld bead modelling compared with the physically based models.

A Unified Approach to Neural Network Modelling

The concept used for developing the neural networks used in the Virtual Welder constitutes a part of a systematic approach to neural network modelling. As basis for this approach, it is realised that *the prediction performance of the neural networks is dependent on the quality of the experimental data. Data of satisfactory quality is a prerequisite for the development of a successful neural network model.* Also, it is realised that experimental work most frequently is an expensive part of a modelling project and it should be aimed to keep the number of experiments to a minimum as well as exploiting already available information in an optimal manner. Finally, it should be possible to return to the experimental planning phase and add new input parameters without having to redo the previous work done in experimental planning. Next, training of the neural networks should be as efficient as possible and modifications of the neural network model should be done without having to redo the work already spent during initial training of the neural networks. This has lead to the development of a methodology for neural network modelling that typically involves the following phases (tasks):

- 1. **Brainstorming and Planning:** The objective of this phase is to gain understanding of the process to be modelled. This involves discussions to decide which are the relevant input and output parameters to be considered. Decisions about the discretization (i.e., number of levels) of the input parameters are also undertaken.
- 2. *Experimental Design*: Based on the information provided in the previous phase, a *design of experiments* (DOE) will be performed by the use of suitable software. This gives a matrix of experiments listed in randomised order to be conducted in the next phase. If experimental information already is available, the software can be loaded with this information. Then, a design matrix is generated which includes the already available experiments.
- 3. *Experimental Work*: This phase involves the main part of the experimental work and preparation of the weld samples. This usually includes a set of screening experiments. Such experiments are needed to determine the operation range of the input parameters. Due to such information, one may sometimes need to involve more input parameters to extend the experimental design matrix.
- 4. *Sample Preparation:* This involves metallographic preparation of the samples (i.e., cutting a cross-section, grinding, polishing, and metallurgical etching).

- 5. *Preparation of Data for Neural Network Training*: The samples and information obtained from the previous phase are measured and then used to generate a neural network training file in electronic format.
- 6. *Training & Analysis of the Prototype Model:* This phase involves both initial training and testing of the prototype model to point out domains in the input parameter space that give predictions with an error larger than accepted for the Virtual Welder. Then, guided experiments are planned to generate additional information to improve the performance of the model in the uncertain regions of the input parameter space. Also, at this stage, work will start with development of the Window's based *Graphical User Interface* (GUI) for the neural network software model.
- 7. *Execution of "Guided Experiments":* This phase involves execution of the guided experiments and preparation of the samples.
- 8. *Refinement of the Neural Network Model*: The information obtained from guided experiments is used for refinement (improvement) of the prediction performance of the neural network.

At best, guided experimentation only has to be executed once. In general, however, several stages of guided experimentation may be needed to achieve a neural network model with the desired predictive capabilities.

Experimental Design and Welding Procedure

This section is related with the experimental approach used in this study. A thorough description of the experimental planning methodology is given along with information about the welding procedure applied during the experiments.

Experimental design (Design of Experiments; DOE) deals with methods for experimental planning that support the user in efficiently obtaining the relevant characteristics of the process [14, 15, 16]. The ideas involved in experimental design are relatively simple but in many cases the statistics involved can be quite difficult. However, such methods are also available to the non-expert via software packages that have built-in routines for a wide variety of design techniques. The output from this process is an experimental design matrix with information on the set of experiments to be conducted.

The keyword in experimental design is planning. Typical decisions that have to be made include:

- Specify the goal of the experiment
- Classify input- and output variables
- Clearly specify assumptions about the process

This is in contrast with the technique often used in traditional experimentation: Frequently in welding (for example in developing a welding procedure), one tends to vary the process input parameters in an unsystematic way; using the results of one run to give guidelines for how to perform the next run. By following this approach, no insight into the coupled influence of the input parameters on the process outputs can be achieved. Thus, when there is no systematic planning of the experiments, there is always a risk of loosing knowledge about a certain important feature of the process and may result in reinforcing false assumptions due to confounding effects in the non-randomized data.

Most experimental designs allow for the estimation of the desired coefficients in the model with fewer (*less than full factorial*) than the full set of experiments that would be included in a *full factorial* design. There is, however, a trade-off between the number of runs, the number of estimated terms, and the quality of the estimation (i.e. the estimated model parameters).

In the literature, two groups of experimental designs are classified. *Classical designs* have desirable statistical properties that make the analysis of the experimental data quite easy. Unfortunately, these designs are applicable only to certain problems and they are inflexible about the number of runs and the factor settings they need. *Taguchi* designs, *full factorial* designs, *fractional factorial* designs, *Box-Behnken* designs, *central composite* designs, and *orthogonal arrays* belong to the classical designs.

Constraints on the region of operability of the factors and other special features of the design situation may prevent the use of classical designs. In such cases the use of an optimal design technique is the only alternative. The *optimal designs* constitute the second group. These designs are non-orthogonal. There are several types of optimal designs (A, D, G and V optimal) each named after the optimization criterion used to determine the set of experimental runs. According to the criterion, the amount of information in the experiments is maximized.

In this work experimental design was used to support the process of establishing a complex model based on neural networks. NA Tech has extensive experience in using experimental design for neural network modelling. In a study performed at NA Tech several classical design methods and optimal designs were examined to determine the best experimental approach for neural network modelling. The initial study included a two level Box-Behnken design and a Taguchi design with three levels. The result of this work clearly indicated that the Taguchi design provided a much better model than the Box-Behnken design.

As part of a continuing overall plan for testing and verification of neural networks, a series of tests were conducted to evaluate the effectiveness of various other experimental designs currently used for statistical modelling. These designs included both three and four level D-Optimal designs. Depending on the number of factors, these designs required similar numbers of experiments as the Taguchi designs. The neural networks generated with the four level D-Optimal designs performed better than neural networks generated from other designs.

However, based on the results of the tests, it was concluded that there could be an improvement on the D-Optimal design of experiments. The result of this work was an "N-Optimal" design method that is optimized for neural network development.

N-Optimal Experimental Design

A refined D-optimal design technique called N-optimal design optimized for neural network applications was developed by NA Tech [1]. It is a proprietary technique. The N-optimal design provides the maximum likelihood of minimizing the error in the neural network while simultaneously using a minimum number of experiments. For the Virtual Reality Welder Training System the primary cost going forward into commercialization will be the addition of new processes and welding procedures. Cost of experimentation will be a significant part of the development cost of the neural network models needed to add new processes and welding procedures. So reduction of the number of experiments is a primary criterion in the N-Optimal design method. When N-Optimal design is combined with another NA Tech proprietary technology, called Guided Experimentation, a neural network can be trained to an acceptable error level. Also, the N-optimal design gives the user the opportunity to add factors and add data from new experiments without having to redo the whole design. This will provide the option to customize the Virtual Welder Training System for any user that has a special welding process or procedure.

This design method is capable of excluding parts of the input parameter space which correspond to possible invalid parameter settings for the process. In the neural network software the "Exclusion Rules" keep track of these omitted regions of the input parameters. Most experimental design technologies cannot tolerate the existence of Exclusion Rules, but the unique design of the N-Optimal method is specifically developed for use with Exclusion Rules. The Virtual Reality Welder Training System software also is designed to incorporate these rules. This will insure that the Virtual Reality Welder Training System will not produce welds with welding parameter inputs that cannot produce a weld. This is a problem which exists with the other major commercialized system.

In addition to using a good design of experiments, it is important to carefully document each conducted experiment. One should keep track of error sources and also register special features observed during the experiments. Based on this documentation, sources of error can be traced and possible bad experiments removed from the data set used to train the neural network. Also, accurate and repeatable measurements are necessary to derive a neural network model that provides an accurate representation of the process that is modelled.

The best way to document each experiment is via automated digital information. For the Virtual Reality Welder Training System automated data recording and digital storage of that information was applied, and is described in the section of this report titled Virtual Welding Experiment Data.

Much effort has been spent at NA Tech to develop an experimentation methodology in which the objective is to minimize the amount of experimental work. This can be achieved if one is able to select *only* the specific data points that completely represent the underlying process. This reduces experimentation costs, network training difficulties, and the risk of network overtraining (overfitting) and hidden node generation. This experimentation methodology is called *Guided Experimentation*.

The guided experimentation method includes three steps. At first, an N-optimal design gives the least possible number of experiments that is needed to train the neural network model. One may often need to perform some screening experiments but these experiments may be included in the set of N-optimal experiments.

Secondly, another group of experiments is selected based on the value of a statistical parameter called the S-parameter. The S-parameter is a specially designed mathematical formula which functions as a maximum likelihood estimator that has shown to be conservative. The error in the S-parameter is never less than the error in the neural network. Depending on the acceptable or allowable error level in the neural network, the value of the S-parameter as evaluated on the original N-optimal data set can be used to pinpoint the regions in the parameter space that need more information about characteristics of the welding process.

The third step is the "refinement" process. The experimental data obtained during the guided experimentation stage are used for refinement of the neural network model to embed into the model the new amount of information represented by the guided experiments. In reality, this is

an iterative process that in practical work has only had to be repeated once for the type of welding models used in the Virtual Reality Welder Training System. After this, training, testing and verification of the neural network model is based on the original N-optimal data set and the additional guided experiments. This is a unique feature of the NA Tech proprietary Guided Experimentation methodology that contributes to reducing the amount of experimental work while simultaneously minimizing the error in the model.

Guided Experimentation

A neural network can be thought of as a "wet blanket" that is to be draped over a set of data points in space. It is pinned at each of the points, but is free to conform to any shape in the regions between points. Using this analogy, it is clear that the first logical conclusion would be that the better "pinned" the neural network, the more accurate will be the resulting model. Stated differently, "if a large set of data points will produce a good neural network, a very large set of data points will produce an even better neural network". This "more is better" philosophy is generally accepted throughout the neural network community.

However, on closer analysis, the problem is really one of selecting the specific data points that represent the underlying process completely. There are actually two methods of achieving this "completeness" of coverage of the process operating space. The first is based on the premise that if there are a sufficiently large number of data points, then the probability is higher that all of the process behaviours will be represented in the neural network training set. This approach is often cited as the only approach that is useful for training neural networks.

However, if it was possible to select only the data points that exactly represented the process, and no more, then several advantages would accrue. First, since experiments are always costly, this approach will yield a cost reduction. Secondly, the neural network training time and difficulties will be reduced if the training data set is smaller. Third, as the number of training examples increases, the likelihood of over training also increases as well as the likelihood of too many hidden nodes required to map the training examples. *Guided experimentation* provides a method for achieving these results by near optimum selection of the necessary training data points while also minimizing the number of unnecessary data points.

The Neural Network Model

A neural network is an empirical approach to process modelling. Such empirical models may be developed from various sources of data, both real and virtual. In general, however, experimental data from actual process operation is the best source of information for developing a neural network model to be used in planning and controlling the production process. Therefore, the quality of the neural network model is a direct function of the quality of the data set. Carefully designed experiments are the key to producing high quality neural network models.

Neural networks $(NN)^1$ are an attempt to develop computer systems that emulate the neural reasoning behaviour of biological neural systems (e.g. the human brain). As such they are, mathematically, loosely based on the internal functioning of biological neural networks [17].

¹ Sometimes also known as Artificial Neural Systems (ANS) or Artificial Neural Networks (ANN).

A neural network consists of a series of nodes (neurons) and weighted connections (axons) that, when presented with a specific input pattern, can associate specific output patterns. In essence, the neural network represents a highly complex, non-linear, mathematical relationship or transform. However, it is not necessary for the developer of such a system to understand the basic underlying physical or scientific principles of a process in order to develop an accurate ANS based process model. In this way it is quite different from other mathematical modelling approaches such as the Finite Element Analysis (FEA) method and more like the traditional statistical or regression type models. The primary difference between neural networks and statistical methods, however, is that neural networks are efficient at extracting patterns from data sets and the data need not be structured in orthogonal arrays.

The challenges in neural network development are to decide how many nodes and connections are needed to model a specific process, how to configure them, and to determine the specific values of the connection weights and the transfer functions that exist within the network. There is no direct known correspondence between the network parameters, its operation, and the problem to be modelled by the network. In this way neural networks are different than simple statistical or regression type empirical models. One of the most successful approaches in developing networks, which has yielded reasonable results, is known as the "backpropagation" method.

In the simplest form, "perceptrons" are one-layered neural networks with nodes that have a hard limit transfer function. This simple architecture places limitations on the computational power of the perceptron. The perceptron learning rule is used to train these single layered networks. Perceptrons may be coupled in series to form multilayer perceptrons (MLP). A more general transfer function than the hard limit function is used in such MLP networks. The MPL trained using Backpropagation are the most commonly used artificial neural networks.

The backpropagation training algorithm was created by generalising the Widrow-Hoff learning rule to multiple layer networks with nonlinear differentiable transfer functions. Standard backpropagation is a gradient descent algorithm. However, using the standard backpropagation training rule may make it difficult to obtain a solution. Numerous modifications of the standard backpropagation method exist.

The learning rules described so far belong to the group of supervised learning rules. This means that they are presented with a set of example input-output pairs (x_i, d_i) and then trained to implement a nonlinear mapping that matches the training examples (datapoints) as closely as possible.

During learning, the outputs of a supervised neural net are used to approximate supplied target (output) values from supplied input variables. *By generalization, however, is meant the ability of the neural network to approximate output data from input variables that are not in the training set.* Generalization is a measure of how well the neural network performs on the actual problem once training is completed; i.e. how good is the prediction performance of the network? The following conditions are typically necessary (but not sufficient) for good generalization:

- The function that the network tries to learn is in some sense smooth.
- The training data set must be a sufficiently large and representative subset of all cases that the network is supposed to generalize over.
- The network is large enough.

In a MLP (feedforward) network, the number of training samples should be approximately ten times the number of weights to achieve satisfactory generalization properties (i.e. avoid overtraining/overfitting).

Since, in general, a neural network performs a highly non-linear transformation from inputs to outputs of the network, it is possible also to 'overfit' the training data: The network behaves correctly for the training data but prediction based on test data, different from the training data, may lead to very bad prediction properties. Such a network is unable to generalize properly. This situation is denoted as overtraining or overfitting.

A neural network that is not sufficiently complex can fail to detect fully all of the nuances of a process in a complicated data set. This leads to underfitting; i.e. the model performs badly for the training data points as well as for the test points.

Limitations of Back Propagation

This "basic" back propagation learning process has several significant drawbacks. First, the optimum configuration (i.e. number and relative location of hidden layers of nodes) cannot be pre-determined by any known method and, yet, needs to be pre-assigned by using an "educated guess" in order to use this procedure. Since the node configuration can significantly affect the operation of the network, this will at best lead to a long series of training re-starts and at worse to no useful network at all.

Secondly, the training process is very slow and no known method for predetermining the learning rate (gain term) will consistently choose an optimum value. As with any search approach, taking steps that are too large will result in overshoot and an inability to find the minimum value in the error of the neural network model and steps that are too small will lead to very long search times.

Third, it has been shown that it generally requires a larger network to "learn" a problem than is required to solve the problem. There are techniques for trimming nodes or connections from a large network, but there is no known method of reducing the size of the network after training that will guarantee optimal net performance.

Finally, learning instabilities exist in nearly every problem that will cause the network to stop learning (converging); at least three types of learning instabilities have been shown to exist. One of these instability types is known as a local minimum. This occurs when a "low" spot is reached on the error surface that is not the lowest error position. Using a geographic analogy, if you are sitting at the bottom of a lake, your local surroundings appear to go up in every direction. If your objective is to always move downward, you will be stuck. However, if you stop at that point, you will never find the bottom of the ocean (i.e. the absolute minimum error point on the surface). This problem has been studied, but for complex processes it is often difficult to overcome this problem when using the traditional back propagation method.

A Novel Neural Network Concept

A new method developed at NA Tech for training neural networks has been shown to overcome many of the known problems with the back propagation method described above. The mathematical construct of a neural network is inherently good at zero-one or on-off type problems (e.g. signal classification). Although the functions typically used as the nodal transfer function in a neural network are continuous functions, they are designed to produce output values that are close to one or zero except in a very small range of input values. But the shape of a weld bead cross-section is a continuous valued problem. This difficulty with neural networks persists in making it difficult to produce accurate continuous valued functional relationships (i.e. weld models) with neural networks.

Figure 13 shows a neural network trained using an error gradient descent type method (e.g. back propagation). This neural network contains a relationship that is very similar to that of the underlying function that was used to generate the training points. However, there is some error in the neural network due, in part, to the transfer function - particularly at points located some distance from the training points. For many modelling applications, particularly where the slope of the response surface is important, this neural network has an unacceptably high error rate.



Figure 13. Neural network trained by the backpropagation training algorithm. The solid line is the neural network model, the dashed line is a function that the neural network is supposed to emulate, and the black dots are the data points used to train the model.



Figure 14. Diagram showing the performance of a backpropagation neural network trained to 4 % error. The overtraining effect is present. This is expressed by good fit in the datapoints but the overall performance of the network is bad.

When the back propagation neural network is "pushed" to converge to very low error levels, or when an excessive number of hidden layer nodes are added in an effort to produce low error, the result is "over training". Figure 14 illustrates the condition of over training. For many real problems, particularly complex process models like welding, the back propagation method will produce either a low accuracy neural network, similar to the example shown in Figure 13, or an overtrained (overfitted) neural network similar to the example shown in Figure 14.

A new neural network architecture was developed by NA Tech several years ago that permits the development of highly accurate continuous valued models. This new neural network configuration, known as the Progressive Neural Network (P/NA), has a completely different hidden node structure than that of the commonly used networks. It is not possible to train this type of neural network using back propagation. The third type of this Progressive Neural Network, known as P/NA³, is capable of highly accurate representation of continuous valued functions (i.e. welding models), as illustrated in Figure 15.



Figure 15. P/NA³ neural network. The underlying function and training data are the same as for the neural networks shown in figures 13 and 14. The neural network model was trained using the NA Technologies P/NA³ algorithm to a mean error of approximately 1%.

Also, a new training algorithm (the D/NA; Delta/Neural-Activity Algorithm) has been developed for the P/NA³ neural network structure to provide accurate modelling of continuous valued processes, including welding, and very fast convergence of the neural network during training. By combining dynamic self-configuration of the neural network together with avoidance of learning instabilities, an operating network is virtually guaranteed for all problems. The network's ability to dynamically configure itself during training will produce a network size nearly optimal for the Virtual Welder Training System. Finally, the P/NA³ networks have good generalization properties and are not hampered with the over-training problems. The resulting neural network structure is ideally suited for all complex non-linear modelling problems, and provides a universal solution to empirical modelling with accurate prediction capabilities for the models in the Virtual Reality Welder Training System.

Testing of Neural Networks

In order to develop a level of confidence for a neural network model it is necessary to thoroughly test the network. Testing and verification provide information that can be used in design and production process planning.

A variety of testing methods are currently used to test and verify the performance of neural network models. Three principal techniques are frequently applied alone or in combination. The first method, known as Train-Test-Verify requires three independent data sets. The first data set is used to train the neural network, the second data set is used to determine the effectiveness of the training process and determine when over training is eminent, and the third data set is used to verify the performance of the neural network. Training is stopped when the prediction error related to the test data set starts to increase while at the same time the error related to the training set is still decreasing.

The Jack-Knife and Boot-Strap methods require less excess data than the Train-Test-Verify method, but all three techniques require additional data in excess of that necessary to train the neural network. All experimentation requires resources, both fiscal and personnel, so the more excess data that is required, the higher the cost of developing the neural network.

NA Tech's methodology for training, testing, and verifying the performance of a neural network, does not require any additional data other than the original neural network training set. This method, when coupled with the N-Optimal experimental design and Guided Experimentation to pinpoint the specific data needed to characterise the process, offers the most cost effective approach to producing an accurate neural network model.

This method involves the use of a maximum likelihood estimator of the neural net predicted outputs, called the S-Parameter. This estimator has been shown to be a conservative estimator; that is, the error in the S-Parameter values is never less than the error in the outputs of the neural network. Additionally, it has been possible to show mathematically that the S-Parameter is a statistic that is t-distributed; it conforms to the student t statistical distribution. *Finally, the calculation of the S-Parameter does not require any additional data beyond the amount necessary to train the neural network.*

Figures 16, 17 and 18 illustrate the use of the S-parameter. Figure 16 shows a neural network developed specifically to have a very poor representation of the underlying function used to generate the training samples. Figure 17 shows a neural network for which the confidence level is approximately 2σ . The confidence level is approximately 99.5% for that size of the confidence interval.

Note that the value of σ is estimated by sampling the output prediction of the neural network at random positions and comparing those values to the values of the known underlying function. This approach is used in testing the S-parameter, but in practice one does not know the underlying function (i.e. the process response) since that is the objective of using the neural network. Figure 18 shows a neural network developed using the N-optimal experimental design method, applying Guided Experimentation, and trained with the P/NA³ neural network. It exhibits high accuracy and a corresponding high level of confidence predicted by the S-parameter test.



Figure 16. A neural network developed specifically to have a very poor representation of the underlying function used to generate the training samples.



Figure 17. A neural network for which the confidence level is approximately 2σ . The confidence level is approximately 99.5% for that size of the confidence interval.

Low Cost Virtual Reality Welder Training System



Figure 18. A neural network trained with the P/NA³ neural network exhibits high accuracy and a corresponding high level of confidence predicted by the S-parameter test

Development of the Neural Networks in he Virtual Welder

The neural networks were trained using the P/NA³ neural network. The neural networks were tested using the statistical S-parameter method to determine the upper bound of the error in the model, and confidence levels for the predicted information. Then the neural networks were integrated into the Virtual Welder Training System software interface. The interface provides the ability to simultaneously observe the weld shape and generate a two dimensional weld cross section shape and weld distortion predictions for the T-joint structural assembly.

The software system also includes a search engine for simultaneously optimizing the weld shape parameters and weld strength, while minimizing distortion in the welded assembly. The system actually consists of multiple neural networks. There are individual networks for the weld shape, weld mechanical properties, and weld distortion predictions. It was more flexible to perform the model development by considering stand alone network structures for the individual phenomena rather than developing one comprehensive structure for all the different outputs. For the user, however, it appears as if there is only one neural network structure.

Training of the neural network for weld shape was relatively straight forward. NA Tech has extensive experience with neural networks for prediction of weld shape. Also, the use of the specially developed "NAMeS" software for capturing the weld cross section pictures makes it possible to efficiently generate the weld shape training file. The performance of the weld shape network is very good. Figure 19 shows the NAMeS software interface used for producing the weld shape data for training the neural network model.

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Figure 19. The NAMeS GUI for measurement of weld shapes.

The Graphical User Interface

The neural network model allows real-time interaction by the user. The user interface, as shown in Figure 20, consists of four windows that can be individually resized and moved around on the computer display. The bottom window is the "Slide Bar Input Window" which allows the user to control the setting of the welding parameters and other input parameters for the neural network models. The use of slide bars facilitates easy entry of input data to the models.

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Figure 20. GUI for the model presented in this work.

Due to the rapid execution time of the neural network models (on the order of milliseconds), the user will see an immediate response to changes of the input variables in the "Output Window" and the "Visual Display Window". The output window contains a number of engineering parameters for classification of geometric features of the weldment. The green and red color coding signals that the computed output variable is within or outside the SPC limits respectively. In the "Visual Display Window", the user can view the weld shape. In the upper part of the compound window are standard program control icons.

Search Optimization and Graphical Features

The search optimisation facility is operated by using the items under the "Search" menu. The relevant parameters in the "Input Parameter Window" that are supposed to be actively used in the search should also be checked. In addition to the check boxes there are "S" marked boxes associated with each of the slide bars for the input parameters. If an input parameter is allowed to vary during the search, the "S" box should be checked. All the other input parameters will then stay at the current values of the slide bars. Under the "Search" menu, allowable ranges for the output parameters (SPC-limits) and target values may be specified along with specification of output parameter weights (i.e. the relative importance of the output parameters during the search). Allowable ranges of the input parameters as well as their costs may also be specified. The SPC limits can be adjusted by using scroll bars as shown in Figure 21. In this way, the objective function for the search may be specified. The search resolution may also be set. The search is performed by first evaluating the performance criterion over the whole input parameter domain according to the selected resolution. Then a gradient-based search is executed in the part of the input domain that so far has the most optimal solution. When the search is completed the input parameters are set to the optimal values and the optimal solution presented in the "Output" and "Visual Display" windows.



Figure 21. GUI with dialog box for setting of the ranges of the input and output parameters

The graphical features under the "DynaGraph (TM)" menu may then be used to display the result of the search. Menu items for setting of SPC-limits and resolution are also available here. Also, the type of surface to be displayed can be selected, and it is possible to select the axes of the graph. Then by invoking the "Generate Graph" item under the "DynaGraph (TM)" menu, the response surface corresponding to the current input parameter setting will be presented. Note that the "DynaGraph (TM)" menu may be used for graphical display of the outputs of the neural networks at any stage during exercise with the software. An example of such a response surface is displayed in Figure 22.

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Figure 22. Typical response surface window

Mathematical Theory for Optimal Designs

St. John [16] gives a very brief introduction to the field of optimal design by the use of a mathematical formalism for stating the optimal criterion used for G- and D- optimal design. In the simplest case, a linear regression model of the following type is considered [16]:

$$y_i = f^T(\underline{x}_i)\underline{\beta} + \varepsilon_i \tag{1}$$

Where I = 1,..., n. n is the number of experiments (observations). y_i is the responses (observations). $f(\underline{x}_i)$ (p x 1) is a vector that depends on the form of the selected response function. \underline{x}_i (q x 1) is a vector of predictor variables. ε_i is a noise term; the process noise is assumed to be noncorrelated (i.e. the variance is σ^2) and have zero mean value. $\underline{\beta}$ (p x 1) is a vector of unknown model parameters. The model can be expressed in matrix notation as follows

$$y = X\beta + \underline{\varepsilon} \tag{2}$$

Now, \underline{y} (n x 1) is a vector of the process responses (process observations). X (n x p) is the design matrix where the i'th row contains the vector $f^{T}(\underline{x}_{i})$. Again, $\underline{\beta}$ (p x 1) is the parameter vector and $\underline{\varepsilon}$ is independently and identically distributed random variables with mean zero and variance as specified above. The experimental region is denoted by χ ; i.e. the vector has to belong to χ . A typical example of the vector $f(\underline{x}_{i})$ may be

$$f^{T}(\underline{x}_{i}) = (1, x_{1}, x_{2}, x_{1}x_{2}, x_{1}^{2})$$
(3)

We see that in this model, two factors (input parameters) x_1 and x_2 are considered. The model is quadratic since terms x_1^2 is included. We also see that the model contains a constant and the linear terms x_1 and x_2 . Finally, an interaction term x_1x_2 is included. In this model, q = 2 (i.e. $\underline{x}_i = [x_1 \ x_2]^T$) and p = 5. If $x_1 = 0.8$ and $x_2 = 0.5$ for the i'th experiment, the design matrix will contain the line (1, 0.8, 0.5, 0.4, 0.64) in the i'th row. Thus, the design matrix is the collection of these rows for every run in the experiment.

At a point $\underline{x} \in \chi$, the predicted response is:

$$y_p = f^T(\underline{x})\beta_e \tag{4}$$

The least squares estimates of the parameters is given by

$$\boldsymbol{\beta}_{e} = (\boldsymbol{X}^{T}\boldsymbol{X})^{-1}\boldsymbol{X}^{T}\boldsymbol{\underline{y}}$$
⁽⁵⁾

where y_p is the predicted response and β_e is the vector of estimated parameters.

In optimal design, the design problems consists of selecting vectors x_i (i=1,2, ...,n) such that the design defined by these n vectors (i.e. the experimental design matrix X) is in some sense optimal. In D-optimal design, the criterion is related with maximizing the determinant of the matrix $X^T X$. The matrix $X^T X$ needs to be non-singular (i.e. no linear dependent rows or columns in the matrix) for the design to be optimal.

For polynomial regression, this is comparable to minimizing the maximum variance for the selected model. To state the criterion by using the linear model notation, we may write:

$$\left[x_{i}(i=1,2,\ldots,n)\right]_{\chi\in\chi}\left(\operatorname{var}(y_{p})(x)\right)$$
(6)

where $var(y_p)$ is the variance of the process response y_p . The regression model presented above is very restrictive since it assumes that the response function is linear in the parameters. St. John [16] discusses how the optimal design theory can be extended to also include nonlinear response functions.

Final prototype system

The primary effort of this project was the development of a fully functional prototype virtual welding system. The design of the system was intended to support the continued development of a sustainable, low cost commercial product. A fully working system has been designed and built. Details of the design, including hardware, software, and user interaction are covered below. An overview of the system is shown in Figure 1 above.

Tracking system

The tracking system is a model V120:Trio commercial Infrared (IR) optical system from NaturalPoint (www.naturalpoint.com). The V120:Trio consists of a rigid bar with three sensor cameras permanently mounted inside. Tracking is accomplished by measuring the motion of small IR reflectors and active IR LEDs. Software supplied with the system uses the location of each IR spot in each of the three camera views to calculate a location for the spot in 3D space. Each object to be tracked uses a known unique spatial arrangement of IR spots. The software is able to differentiate between objects based on this arrangement and to calculate the angular orientation of the objects, providing 6 degrees of freedom (6 DOF) tracking for multiple objects.

A combination of active LEDs and passive reflectors is used for tracking. The LEDs are small (3mm) with a wide field of view ($\sim 160^\circ$), with a nominal emission of 850 nm. The reflectors are small ($\sim 3/16$ ") hemispheres covered with "sparkles". They are illuminated by IR LEDs contained

in the sensor bar. The LEDs and reflectors create small "dots" in the sensor image. Image processing algorithms in the tracking software follow the motions of all the dots and calculate their locations.

The tracking system captures the location of the base holding the welding test plate, the torch, and the helmet. The base is only tracked during system setup in order to align the test plate with the virtual model. The system can track the helmet and torch anywhere in the normal range of positions while in use.

When the system is first set up after transporting there is a one-time calibration and alignment procedure which must be completed. This is done using software supplied with the tracking system. After this is done the tracking is automatic and handled by the simulation system. There is no direct user interaction with the tracking software.

Integrated tower

There are two major hardware components of the virtual welding system, the suitcase welder controller and the integrated tower. The tower has a base platform which holds the welding test plate. The base has a holder for the welding torch. The holder positions the torch so that the system can self calibrate on start-up. The tower also has an arm extending upwards to hold the tracking system bar. The arm is retractable and the base is hinged so it can be folded up against the tower for shipping. On the front of the tower there is an LCD touch screen for user interaction with the system. Inside of the tower there are power electronics, speakers, and a wired/wireless Ethernet hub for network connectivity between system computers. The entire tower unit weighs less than 30 pounds.



Figure 23. Welding controller case



Figure 24. Control panel

Suitcase controller

The other major hardware component is the suitcase welder controller. The controller box uses the container of a standard suitcase style wirefeeder/controller as shown in Figure 23. The case is delivered without the wirefeed mechanism, but with the welding controls and LCD display panel still intact, Figure 24. These controls are used as part of the simulation system. Inside of the case there is an industrial PC mounted where the wirefeeder would normally be. See Figure 25. The welding simulation software and the virtual display graphics run on this PC.



Figure 25. PC mounted inside case

The electronics for the welding controls and display are contained on the blue circuit board seen at the top of Figure 26. The controls and display are actually interfaced with the welding simulation software through the use of a National Instruments multifunction analog/digital I/O controller. The controller is the white box on the right in Figure 26. The person welding uses the buttons and dials on the case to set the desired current or voltage and the wirefeed speed. These inputs are read in to the simulation system and then output back to the display panel. The I/O controller also handles the torch trigger input and vibrator output. Display graphics and sound are output directly from the PC. The blue modules on the left in Figure 26 are DC power supplies used to drive the LEDs for the base, helmet, and torch for tracking.



Figure 26. Electronics and digital interface

Torch

The welding torch is a real GMAW torch that is typical of shipyard equipment. It has been modified to add IR reflectors for tracking. See Figure 27. A small vibrator device is mounted inside of the torch and is driven by the welding simulation in order to give tactile feedback when a weld is being made. The trigger on the torch continues to serve its normal function of initiating the weld. A delay is built into the simulation after the trigger is pulled to mimic the gas purge and wire delivery delay of a real GMAW system. All of the electronics in the torch are handled by the wires that come in the standard cable assembly so that no additional wires are required. The torch cable is attached to the suitcase controller by a quick disconnect fitting so that it can be easily removed for shipping.



Figure 27. Welding torch



Figure 28. Welding helmet IR reflectors



Figure 29. Welding helmet display

Helmet/Display

The welding helmet is a standard light-weight helmet with the protective darkening lens removed and replaced by a black shield. See Figure 28. IR reflectors are mounted on the front of the helmet for tracking. The virtual world is displayed to the user through a lightweight "eyeglasses" style monitor with separate displays for each eye, as shown in Figure 29. The display is permanently mounted inside of the helmet. The user puts the helmet on and tilts it up and down for viewing just like a regular welding helmet. The display has a resolution of 640 x 480 pixels at 60 Hz, with separate screens for each eye. The display can be used in 3D (stereo) mode but is currently displaying the same image to each eye.

Sound

The virtual welding system uses a unique approach to provide accurately simulated sound during welding. Real-time audio was collected as part of the measured data during the welding of all the test specimens. The audio track for each weld was stored with the other input parameters. After an analysis of all the audio data, each sample set was processed to extract two separate signals. One signal represents a composite baseline or average that is common to all of the welds. The other signal represents the unique highlights that are characteristic of each individual weld. Each highlight signal is tied to a specific data point used to build the neural network for weld simulation.

All of the audio signals were converted to digital form for processing. Each signal was further time-sliced into small discrete chunks. These short discrete sound bits can then be recombined using a randomization algorithm to create an unlimited length sound track that is realistic, but not noticeably repetitive.

When the simulation runs the baseline welding sound is generated as the background track. On top of this a second track is added with the highlight sounds specific to the weld being made at each instant in time. Each of these tracks is built using the randomized time-slicing algorithm. The final sound gives a very accurate representation of real welding, with all of the characteristic subtleties associated with actual performance. In this way the sound responds accurately to the user's action, providing interactive feedback on welding quality. Sound is delivered by speakers located inside of the tower.

User Interaction

Users of the virtual welding system log-in using the touch screen on the front of the system tower. Users have an ID which has been created in the system by the welding instructor or an administrator. The user's ID is selected from a drop-down menu with a list of all known users and then the user enters a PIN number on the touch screen key pad. See Figure 30. A wireless keyboard and mouse are also available to be used for login and system interaction instead of using the touch screen.

Low Cost Virtual Reality Welder Training System



Figure 30. User login screen

The initial view shows the weld test plate in the center of the image. The same view is displayed on the tower touch screen and in the welding helmet goggles. The welding torch is also displayed if it is held in the visible region around the weld test plate. The torch motion is tracked by the system so the torch will appear in its actual position relative to the test plate as it is moved. A number of icons appear in the upper left corner of the display. These are clickable buttons that allow the user to adjust settings, start a new weld, or exit from the simulation.



Figure 31. Welding view

At this point the user can start a new weld by clicking the forward arrow button in the upper left. When the torch trigger is squeezed the arc will start after a brief delay for initial shielding gas purge. When the arc starts the screen will immediately go dark, mimicking an auto-darkening helmet lens. The arc and area surrounding it will become visible as welding progresses. See Figure 31. The view shows the wire feeding out from the torch, the arc puddle, and the deposited weld bead as it is formed.

The user has control over a number of different settings. These can be adjusted through the Tools menu, which is activated by clicking the tool icon in the upper left. Adjustable settings include the weld type, voltage, wirefeed speed, viewing direction, and welding direction. The Tools menu is shown in Figure 32. At this point there is only one weld type available – a T fillet in the

horizontal position. As other weld procedures are added they will appear as options in this list. The voltage and wirefeed settings can be modified here and can also be set using the normal dial controls on the front suitcase welder unit. Welding direction can be set to either left-to-right or right-to-left to accommodate use by right handed and left handed welders. The viewing direction can be set to an isometric view looking to the right or looking to the left. This allows for a correct view for either welding direction or for a user preference of "pushing" or "dragging" the torch.

Boose and	
in Kaesar Andering Admendi Teo	-
Student: 9	
Weld: T-Fillet - Horizontal - 3/16th ?	
Volts: 31.2 WFS: 497 ipm << Left	
Start A New Weld Visual Display	
% Good: 0 Status: Travel Speed	
 Track Helmet Show Messages 	
TS Avg: 0 Set Indicators	
Teach Torch On	

Figure 32. Tools menu

After a weld is complete the Tools menu will display a value for "% Good" for the finished weld. This number tracks the percentage of the length of the weld where the user kept within the specified parameters for the value listed in the Status field. The system measures and records all of the input parameters, but only the one selected parameter is used for calculating the "good" score. The Status field can be set to any of the measured input values in order to focus training on one parameter at a time. The % Good score provides a simplified objective evaluation mechanism. This score can become the basis of light-hearted competition between students as they train.

The quality of the finished weld is also represented in the color coding of the weld bead in the displayed image. The color coding takes into account the single parameter selected in the Status field as well as all of the other measured input parameters. If all of the input values are in the correct range then that portion of the weld will be shown in green (good). If the value specified in the Status field is in the correct range, but some other measured value is out of range, then that portion of weld will be shown in yellow (warning). If the value in the Status field is out of range and other values are also out of range then that portion of the weld will be shown in red.

Significant improvements have been made to the visual display of the simulation during welding, as seen in Figure 31 above. Although the basic view is reminiscent of the earliest prototypes from phase 1 of this project, there have been extensive changes in the underlying software. The simulation model has been updated with real input data from the measured welding experiments. The timing loop and tracking interaction have been improved and made more robust. The detailed graphics and lighting have also been enhanced to make a more life-like image and a realistic depiction of the arc puddle during welding.

Low Cost Virtual Reality Welder Training System

Student: 9	
Weld: T-Fillet - Horizontal - 3/16th ?	
Volts: 21.3 WED 199	
Start P Travel and Work Angles (Teach Torch) OK P Travel Speed (Red Laser Line)	
% Goo P CTWD Indicator (Red Arrow) Cancel	
T Weld Size (Chalk Lines) 0.25 Inches	
TS Avg: 0 Set Indicators	
r Teach Torch On	

Figure 33. Control of optional prompts



Figure 34. Visual cues displayed

A number of instructional prompts are available during the weld simulation to help a new welder master proper welding form and technique. Four different visual cues can be turned on or off to guide the student. There is a wireframe image of the welding torch, the "Teach Torch," which is drawn on top of the actual torch and always shows the correct angles. A red line is drawn which moves along the weld seam at the ideal rate to indicate the correct travel speed. A red arrow is superimposed on the torch pointing either toward the work piece or away from it to indicate the correct contact tip to work distance. Finally, a white chalk line is drawn along the top and bottom pieces of the test plate to indicate the correct sizes of the vertical and horizontal leg lengths. This helps the student to make a weld that is the right size for the given weld specification. Each of these visual prompts can be turned on or off independently as needed to guide the student as they start out and begin to develop consistent skills. The controls are shown in Figure 33. The visual representation of all the helping cues can be seen in Figure 34.

Additional detailed information on the use of the virtual welder system is given in the User Guide, included here as Appendix B.

Teacher Information System

Detailed information about every weld made with the virtual welder system is collected in a database. This data is accessed through a separate application called the Teacher Information System (TIS). The database is stored on the embedded computer inside of the suitcase welder controller, but the TIS application is typically run on a separate computer which is connected to the system via the wired/wireless network router in the tower. The TIS provides functionality to review every aspect of a weld. It is meant to be used to help students analyze their technique and the resulting quality of their welds.

Teacher Information System - Rep	orting	
	Student To E valuate Demo Student Veld To E valuate 0000000190 Refresh Distance Along Weld Positioner	3D Weld Close Playback Weld
Travel Speed Data Value: 22.000	Set SPC Limits Parameter Selection: Travel Speed	TS TA WA CTWD OFFSET
14.000 -1.091	Distance Along Weld	7.805
Vertical Leg Length Data Value: 7.315 8.973	Set SPC Limits Parameter Selection: Vertical Leg Length	TS TA WA CTWD OFFSET
6.905 -1.091	Distance Along Weld	7.805
Horizontal Leg Length Data Value: 7.287	Set SPC Limits Parameter Selection: Horizontal Leg Length	TS TA WA CTWD OFFSET
7.287	Distance Along Weld	7.805

Figure 35. Teacher Information System screen

After a weld has been made it can be reviewed in the TIS. Refer to Figure 35 to follow this description. The desired student and the desired weld to review are selected using the drop-down menus. Welds are numbered sequentially from 1 to n in the order they were made. The three graph bars in the bottom half of the TIS show the values of the selected parameters along the entire length of the weld. The parameters being displayed in the graphs can be set using the Selection pull-down list. The user input parameters, i.e. travel speed (TS), travel angle (TA), etc, can be selected using the buttons on the right. To display the data values for a particular point along the weld the user can either drag the Distance slider above the graphs or click and drag the mouse to a point inside any of the graphs. A vertical line is drawn in the graphs to indicate the selected point, and the corresponding data values at that specific point in the weld are displayed above each graph. The green band in the center of each graph bar shows the range of values that are acceptable for the given weld specification.

A cross section view is displayed in the upper left of the TIS window. This shows a graphical representation of the shape of the weld at any selected point along the length of the bead. The shape of the weld is precisely simulated based on the weld settings and the measured input values at that exact time. This provides a unique tool for evaluating the quality of a weld, being able to see the shape of the weld beneath the surface of the material. This can help a student better understand the effects of variations in welding technique. Changing the work angle of the torch may affect a visible feature of the resulting weld, such as leg length. With this cross section display it is possible to see hidden features that are also affected by the same change, such as penetration and throat.

The TIS also enables a weld to be played back in a 3D viewer. The "3D Weld" button will launch a viewer window and the "Playback" button will recreate the weld just as it was originally made by the student. Using the distance slider it is then possible to move along the weld or to any particular point to see the bead being formed and see the motion of the torch. This is another tool that can be used to review performance and to reinforce proper welding technique.

The TIS has some administrative functions for managing user accounts and for managing the weld database. The weld database should function correctly for long periods of time without any required maintenance or attention. The intended use of the administrative tools is the creation of new user accounts. Users must login to the virtual welder with a particular user ID. It some cases there may be a shared "guest" user that allows people to use the system casually. However, every weld is recorded and tracked by the user ID. In order to track the progress of individual students they should each be given a user ID and make use of that ID when they weld.

Field testing

At the time of issue of this report three virtual welder systems had been deployed to shipyards and welding schools. The three locations were Electric Boat Quonset Point welding school, Norfolk Naval Shipyard welding school, and Red Rocks Community College (Lakewood, CO) vocational welding program. The original project goal was to deploy between 15 and 20 prototype systems. This goal was not met due to project delays and lead times in buying some of the parts for the prototypes.

NA Tech plans to continue building and deploying prototype systems after the formal completion of this project on 29 February 2012. Deliveries are already planned for early March 2012 to Bollinger Shipbuilding, Lockport, LA, and VT Halter, Pascagoula, MS. The system at Electric Boat Quonset Point is also planned to be moved to Electric Boat Groton in March. Later deliveries are also expected to NASSCO, San Diego, CA, Vigor, Seattle, WA, and Pearl Harbor Naval Shipyard, Honolulu, HI.

All of the participating NSRP shipyards were contacted about the possibility of hosting a prototype virtual welder system at their welding schools or training facilities. All of the public naval shipyards were also contacted. In addition, a number of other non-shipyard welding training institutions expressed interest in hosting prototype units. The full list of initially planned deployment locations is given in Table 2.

Site	Location	Status
Norfolk Naval Shipyard	Portsmouth, VA	Delivered
Electric Boat Quonset Point	North Kingstown, RI	Delivered
Red Rocks Community College	Lakewood, CO	Delivered
VT Halter	Pascagoula, MS	Planned
Bollinger	Lockport, LA	Planned
Electric Boat Groton	Groton, CT	Planned
Todd/Vigor	Seattle, WA	Potential
Pearl Harbor Naval Shipyard	Honolulu, HI	Potential
NASSCO	San Diego, CA	Potential
University of Alaska Southeast	Ketchikan, AK	
HII Ingalls	Pascagoula, MS	
BAE/Atlantic Marine	Jacksonville, FL	
HII Newport News	Newport News, VA	
Portsmouth Naval Shipyard	Kittery, ME	
Milwaukee Technical College	Milwaukee, WI	

Table 2. Planned prototype locations

The intent of deploying prototypes was to collect feedback on the performance and use of the virtual welding system. Even though only a few prototypes were delivered during the project we were able to collect a significant amount of feedback from these locations. The initial delivery of a system to Electric Boat Quonset Point and the early contact with Red Rocks Community College led to a long list of changes and improvements which have already been incorporated into the prototype design.

When the prototype systems were delivered to each location the local welding instructors were given a one-page evaluation form. These evaluations were to be filled out by each person who tried the virtual welder system. The intent was to gather feedback from the users on how the system performed and whether it seemed useful for learning how to weld. A minimal amount of background information on the users was also collected in order to correlate the results. Background included welding experience, age, and exposure to other virtual welding systems. The user feedback form is shown in Figure 36. In addition to questions rating various aspects of the system, there was space for recommended changes and general comments.

aund	Welding expe	rience:	beginne	er/i	ntermedi	iate	/ expert	Į.
ackground	Location:				Time/sh	ift:		
	Age: under 3	30 / 30-4	5 / over	45				
	Have you trie	d other we	lding sin	nulato	ors before	e?	yes / n	0
	Lame	1	- 2	- 3	4	ł -	5	Cool
General	Waste of Time	1	- 2	- 3	4	-	5	Useful
mnression	Boring	1	- 2	- 3	4	+ -	5	Fun
II+ F	Artificial	1	- 2	- 3	4		5	Realistic
	How similar v	was this vir	tual wel	ding t	o real w	eldin	ıg?	
	Feel	1	- 2	- 3	4	ł -	5	
	Arc/Weld pool	1	- 2	- 3	4	- 1	5	
	View	1	- 2	- 3	4	- 	5	
valuation	Sound	1	- 2	- 3	4	- 1	5	
	Useful for lea	rning how	to weld?	,				
	No	1	- 2	- 3	4	-	5	Very
	How many w	elds did yo	u make?		1 / 2-	10 /	/ >10	
Changes you v	vould recommend:							
Comments:								

Figure 36. User feedback form

A summary of the user comments received is given below:

- Users were mostly beginners, with only a few expert users (instructors)
- There was an even distribution of ages
- Only a couple of users had experience with other virtual welding systems
- The average "General Impressions" score was 2,
- The average "Evaluation" score was 1.5

- The average "Useful for learning to weld" score was 1.25 (These were on a scale of 1 to 5, with 1 being more negative and 5 being more positive)
- Many of the text comments mentioned that the system was not realistic enough

At some point during the testing period at each location a more in-depth interview was conducted with the welding instructors overseeing use of the system. The interview was meant to collect feedback on the usefulness of the system from the instructors' point of view. Questions were asked about how the students responded to using the virtual welder and how it might fit into the welding training curriculum.

The primary comment from instructors was that it was difficult to make welds that the system considered "good" welds. Even when they were very carful to use correct technique they could not produce welds that had much "green", or good weld. The instructors also commented on the need to include additional weld procedures to cover a broader range of training.

A limited number of evaluation forms and instructor interviews were collected before the formal end of the project. As additional prototypes are deployed to more locations evaluation forms and interview results will continue to be collected. The authors intend to submit an addendum to this final report at a later date which will include a summary of these results.

Plan for Commercialization

NA Tech fully intends to continue development of the virtual welder even after the end of this NSRP sponsored project. Their vision is to establish the virtual welder as a fully supported commercial product. To this end NA Tech has entered into discussions with a large welding equipment supplier to pursue possible licensing agreements and expanded product development opportunities. Support from a larger company would provide access to further development funding and an established market presence.

NA Tech has a long history of fielding and supporting commercial welding technology products. An initial plan has been drafted which lays out the basic business model and costs associated with the virtual welder as a marketable product. NA Tech will continue to pursue this market opportunity, whether on their own or in partnership with a larger welding equipment supplier. The long term goal is to provide a low cost virtual welding system for sale back into the shipbuilding community as well as the larger welding training community.

The final system ended up costing more for hardware than originally expected due to issues with the tracking system. The actual material costs for each of the prototype units is about \$8000. The final system design should be able to be marketed as a sustainable commercial product for a cost of about \$15,000. This cost is also based on the limited quantity of hardware purchased for the prototype units. As a production item the unit cost should be able to be reduced while still maintaining commercial viability.

Discussion

During the execution of this project a number of issues have been raised and considered that were not addressed within the scope of work, but that have potential significance to the future success of this and other virtual welding systems. These issues are discussed here with enough background to get the reader engaged, but without specific conclusions given.

Low cost sensor technology

In the original plan of work for this project, sensing and tracking was going to be accomplished using low cost consumer devices – the Wii remote. While this approach was demonstrated to be technically possible it was not found to be adequate for a production use tool. As a result, the tracking system went through a number of iterations until it ended up being a relatively expensive commercial tool. The per-system cost for sensing went from ~\$150 to over \$2000. Camera based tracking continues to be an aggressive area of development in the consumer gaming community and in the computer vision community. In the time that this project went from considering the Wii to rejecting the Wii, the newer XBox Kinect has come to market. The Kinect is another ~\$150 item that might have the capabilities required to build a working welding simulator. It is also likely that with some more effort it would be possible to identify a software solution that would enable robust tracking with low cost generic USB cameras.

There will probably always be inherent tension between "inexpensive" sensor systems and "easy to implement and always work" sensor systems. In this era of rapid innovation in electronics it may not be too long before the inexpensive systems are robust enough or the commercial, ready-to-use systems are cheap enough that it will not matter in the final product cost.

Low cost display technology

Lightweight head mounted display (HMD) systems fall into two broad categories. There are consumer devices that are low cost and limited resolution, and there are commercial and military devices that have higher resolution and picture quality at a much higher price. This project helped sponsor some research to look for unknown intermediate level devices. None were found.

The research done also looked at the cost and difficulty of building a novel HMD from other existing display systems. The rise in popularity of large-display phones and tablet computers has led to the availability of medium resolution LCD panels in small form factors. Another emerging product is the hand-held projector or pico-projector. Both small LCD panels and small projectors have the potential to become the basis for new HMD designs.

20 years of experience with HMDs indicates that there is still a very limited consumer market for these devices. With the recent drop in retail prices for large format LCD panels (HDTVs and computer monitors) it seems unlikely that there will be any significant market for consumer level HMDs in the near future.

Virtual welding is probably the ideal application for a low cost HMD. Since welders always wear helmets they are used to putting something on and taking it off. The limited viewing area of a helmet lens is very reminiscent of a display screen. The visible scene during actual welding is

also so obscured and of limited contrast that it might be acceptable to use lower fidelity displays than what is required for other applications. Perhaps the virtual welder will drive the development of new low cost consumer level display devices and create a new class of products.

Augmented reality system

With the advent of web-cams, low cost computer based camera systems are now readily available. Development in the computer vision community has also made it relatively easy to manipulate cameras and video streams with software. A logical extension of the current virtual welder system would be to make an augmented reality system that captures live video and mixes the image with the simulated weld. Early work in this area was done 10 years ago under the TEREBES project in Europe.

Augmented reality would simplify some of the development for virtual welding systems. Live video could be used to capture and display the background scenery before welding. This would eliminate the need to build a 3D virtual environment to replicate the real world.

Simulated weld vs. weld game - accuracy vs. realism for training usefulness

The use of a computer based simulation that displays a dynamic 3D environment and is controlled by moving a hand-held device seems very much like a video game. Most of the users of the virtual welder who are younger than 30 probably approach the system as though it was a video game. The virtual welding system was designed as a weld simulation tool. There are some distinctions between a simulation tool and a video game.

Although a video game usually involves some type of simulated behaviors and a simulation tool often employs some game-like behaviors, there is a difference in focus. Games usually focus on visual realism and special effects. Games also involve some higher level goal-oriented strategy. The welding simulation is focused on reproducing an accurate representation of the weld being made. The accuracy of the weld, based on the measured inputs, is the primary design goal.

It would be a good thing if the virtual welder looked and felt exactly like real welding. However, it would not be good if the look and feel were correct, but the resulting weld was incorrect. Students familiar with video games may dislike the virtual welder because the graphics are not as life-like as they expect. However, instructors should like the system because the simulated weld will be very accurate, showing exactly what would be achieved in a real weld.

User engagement and competitive use

The virtual welder system provides the user with a composite score for each weld. The score is based on what percentage of the weld was made with all of the measured inputs inside of their allowable ranges according to the weld specification. We have found that when two or more people are using the system together there is a tendency to compete to see who can get the higher score. Although this competitive behavior might be expected of younger users, along the lines of video games, it has also been observed with older users. We believe that this friendly competition can be useful as a learning mechanism for welding training.

This competitive behavior is a means for students to become more engaged in the learning process. It encourages them to do more practice welding and challenges them to improve their technique. Competition is not often found with "real welding." This is likely due to the subjectivity involved in scoring the relative quality of two different welds. The virtual welding system not only provides an objective score, but it also makes it much easier to make more welds. Being able to do more practice and being able to quickly repeat a challenge fosters the competition. Competition should be good for learning for learning how to weld better.

User engagement and active experimentation

The virtual welder system provides students with the opportunity to make as many welds as they want in a relatively short period of time. There is no scrap and no limit on test plates. The system also provides a quick analysis of the resulting welds with no need to cut and bend or cut, polish, and etch. There are indications that this combination of quick repetition and easy analysis leads some students to engage in active experimentation with the welding process. Some students will make a series of welds and vary one aspect of their technique with each weld to see the resulting effect in the weld shape and quality. Although some of the resulting welds are poor, there is a learned cause and effect. The poor weld result becomes clearly associated with the improper technique that caused it. This experimentation should help students to gain a better understanding of proper weld technique and better appreciation for following approved weld specifications.

Conclusions

A fully functional virtual welding system has been developed and demonstrated in use at multiple welding training centers. The system allows users to make welds and evaluate the quality of those welds. The system includes a complete software suite for creating welds, managing any number of different users, and tracking and evaluating weld quality and welder progress over time.

The virtual welding system is transportable and can be set up in about an hour. The entire system can be packed in two airline shippable containers. When set up, the system consists of two major components, each weighing less than 30 pounds. It can be set up on a standard classroom desk or table and requires only standard 110v power.

The primary objective of this project was to develop a low-cost system that would be affordable for shipyards and other welding training institutions. The means to achieve this was to make use of consumer level equipment and repurpose existing weld monitoring software for use in simulation. The final system ended up costing more for hardware than originally expected due to issues with the tracking system. The final system design should be able to be marketed as a sustainable commercial product for a cost of about \$15,000. While more than originally expected, this is roughly 1/3 the cost of some other virtual welding systems.

Initial feedback from users of the new virtual welder system indicates that further improvements are required. Most of the users thought that the feel of the torch and the view in the display were not realistic enough. Some instructors were concerned that it was too difficult to make "good" welds. A new neural network weld model is being developed that attempts to broaden the range of acceptable input values. This may make it easier to achieve good welds. The issue of perceived realism has been a design concern from the very beginning, and will continue to be addressed.

NA Tech fully intends to continue development of the virtual welder, whether on their own or in partnership with a larger welding equipment supplier. An initial plan has been drafted to establish the virtual welder as a fully supported commercial product. The long term goal is to provide a low cost virtual welding system for sale back into the shipbuilding community as well as the larger welding training community.

The virtual welding system was built with a single weld model and can currently only produce "T" fillet welds in the horizontal position with the GMAW spray process. This was according to the project objectives of building and demonstrating a working prototype system. Additional welding processes, joint types, and out of position welds could be added to the system with minimal additional effort. Each new process or configuration would require the welding and measuring of a set of test welds to generate data for a new neural network model. The intended next steps for this system are the addition of SMAW ("stick") welding and out of position welds using the GMAW pulse process.

The effort to convert the tracking system from Wii remotes to some other low cost device ended up consuming more time and effort than originally expected. If this conversion had not been necessary then the project would likely have completed work on a number of different welding processes and configurations. The virtual welding system enables early exposure to welding in a very approachable, nonthreatening environment. The system can easily be used in a standard classroom. There is no requirement for personal protective equipment and there are no consumables or extra power or ventilation requirements. Due to this accessibility it is believed that the system will be useful for early screening of prospective welders. It should help to determine whether a person has the manual dexterity for successful welding. It could even be used to test for any interest in welding among those who have had no exposure to it.

There is still minimal conclusive evidence on the overall benefit of virtual training for welding. However, there is definite evidence for the benefit of virtual training in general for other types of physical activities. There is also some evidence from other reports that virtual welding training improves long-term muscle memory and leads to earlier mastery of the welding process. Perhaps the availability of more, lower cost virtual welding systems will spur additional research on the effectiveness of virtual welding training.

The current virtual welding system does offer some immediate and unquestionable advantages over real welding. It definitely provides trainees with the opportunity to make more welds than they could make with real welding. There is no need for test plates or scrap steel and there are no gas or high power electricity needs. Students can weld over and over again at the press of a button to practice and hone their technique. They also have immediate feedback on the quality of the welds being made. This is something that is almost impossible in real welding. An instructor may offer an expert opinion if they take the time to watch a weld being made, and a bend-back test will give some indication of weld quality. Together, though, they do not equal the ability to see immediate cross sectional images of a finished weld and to see internal features such as penetration or lack of penetration. The virtual welder provides 100% instructor feedback on every weld for every trainee.

There is anecdotal evidence that the use of virtual welding encourages more active participation in the learning process. There are reports of users engaging in experimentation with the welding process. With "real" welding using physical test plates students are pressured to make every weld a good weld. With the virtual welder there is no penalty for quickly making some "bad" welds and then throwing them away. Some students are intentionally exaggerating aspects of their technique, whether torch angles or travel speed, in order to see the effect in the simulated weld. Being able to see the cross section and the inside of the weld right away, students can experiment with cause and effect. Since this can be done quickly, over and over again, it does not take away from their time practicing and making "good" welds.

A usable low-cost virtual welding system has been created for use in welding training. The current prototype version represents a baseline for functionality and design, serving as a proof of concept. It is expected that the current design will be further developed and enhanced into a marketable commercial product. We believe that if a low-cost virtual welder product were available that it would find an eager market among equipment manufacturers, trade schools, and technical colleges, in addition to the initial focus of shipyards and the shipbuilding community.

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Appendix A – Technology Transfer

During the course of this project the interim results were presented at a variety of NSRP and other shipbuilding related meetings. These meetings were well attended by representatives from all of the larger and mid-tier shipbuilders in the U.S. At some of these meetings a prototype virtual welder was available for hands-on testing. A list of all the presentation venues is given in Table B-1. In addition to presentations, prototype versions of the final virtual welder system were deployed to a number of shipyard welding schools and other welding training institutions for in depth testing and evaluation. A list of prototype locations is given in Table B-2.

Event	Location	Date
NSRP All Panel Meeting	Philadelphia, PA	15-17 September, 2009
AWS Shipyard Conference	Metairie, LA	16-17 June, 2009
NSRP Joint Panel Meeting	Ponte Vedra, FL	21-22 April, 2010
NSRP Joint Panel Meeting	Washington, DC	30 September, 2010
SNAME Ship Prod Symposium	Bellevue, WA	5 November, 2010
ShipTech Conference	Biloxi, MS	14-15 March, 2011
NSRP Joint Panel Meeting	Ann Arbor, MI	13 April, 2011
NSRP Joint Panel Meeting	San Diego, CA	3 May, 2011
NSRP Day at NAVSEA	Washington, DC	22 September, 2011
NSRP All Panel Meeting	Newport News, VA	4-5 October, 2011
SNAME Ship Prod Symposium	Houston, TX	17-18 November, 2011

Table B-1.	List	of 1	meeting	presentations
\mathbf{I} able \mathbf{D}^{-1} .	LISU	UI I	needing	presentations

Table B-. List of prototype locations

Site	Location	Status
Norfolk Naval Shipyard	Portsmouth, VA	Delivered
Electric Boat Quonset Point	North Kingstown, RI	Delivered
Red Rocks Community College	Lakewood, CO	Delivered
VT Halter	Pascagoula, MS	Planned
Bollinger	Lockport, LA	Planned
Electric Boat Groton	Groton, CT	Planned
Todd/Vigor	Seattle, WA	Potential
Pearl Harbor Naval Shipyard	Honolulu, HI	Potential
NASSCO	San Diego, CA	Potential

Appendix B – Virtual Welder System User Guide

The Virtual Welder System User Guide is attached as a separate PDF document:

"Virtual Welder User Manual.pdf."