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# Automated Workpiece Localization for Robotic Welding

Mabaran Rajaraman
Department of
Mechanical Engineering
mabaran@cmu.edu

Michael Dawson-Haggerty
Robotics Institute
mdawsonh@andrew.cmu.edu

Kenji Shimada
Department of
Mechanical Engineering
shimada@cmu.edu

David Bourne
Robotics Institute
db@ri.cmu.edu

Carnegie Mellon University
Pittsburgh PA 15213

*Abstract* — **Precise knowledge of a workpiece's position is essential to robotic manufacturing. This often requires design and use of special purpose fixtures and programming between manufacturing operations. Our goal is to remove these requirements and automate the discovery of position (localization) of the workpiece. For quick setup and localization we have augmented the end-effector of the robot with a laser projector and a laser displacement sensor. The laser projector guides the worker in initial fixture and workpiece placement and the laser displacement sensor acquires a 3D point cloud of the workspace. The point cloud collected after scanning the workspace is processed to provide a sparse outline of the workpiece. This outline is then compared to the computer aided design (CAD) data of the workpiece to estimate a transformation between the actual and planned position. This estimation is made by using an iterative closest point algorithm. Multiple searches are run using different seed points to improve the chance of finding the best fit while maintaining low run times. In this paper, we have used flat weldments as test cases. In our experiments we were able to localize and weld workpieces with significant time savings against current practices in manual welding.**

## I. INTRODUCTION

Robotic manufacturing in mass production industries has replaced manual labor in a wide range of tasks. However in industries manufacturing products with shorter life cycles, manual labor is still dominant. Long setup times for a new part or assembly usually outweigh the advantages of automation for low volumes. This is especially prevalent in the welding industry where setup time of the weldments account for more than 95% of the total process time; even when using manual labor. Most of setup time is spent on picking the right workpieces and positioning them in the workspace for welding. The worker has little knowledge of how the weldments are setup and needs to lookup outlines or prints to make decisions. This adds to the delay and cost of welding.

Setup times are even longer when robotic welding is required due to additional time spent on precise fixturing.

A typical automated welding setup requires the following steps

1 Design and sequence of workpieces
2 Preparation of workpieces
3* Path plan of robot to execute weld
4* Placement and fixturing of workpieces
5* Weld execution by robot

* steps modified by our system.

The welding process can be completed in shorter time if the setup and planned procedures (steps 1-4) are expedited. Since steps 1 through 3 can be preplanned, the major expense is incurred in placement and fixturing (step 4). In our work we preplan steps 1 through 3 and execute step 4 (placement) quickly with our robot guided placement procedure (discussed in Section III). However, a quick setup also introduces uncertainty in the position of the workpiece. This makes it difficult to automate using typical robotic setups where precise knowledge of workpiece position is required.

In this paper, we present a solution to take advantage of shorter setup times from more flexible fixturing. By measuring precise position information of the workpiece after placement, we can verify that tolerance requirements are met and re-plan execution paths (steps 3-5).

Prior work by [1] introduced a concept of augmenting robots with compact laser projectors to guide humans in workpiece setup for automation. Their goal was to significantly reduce the setup times involved in task-specific fixturing for automation. In our system, we have implemented their proposed approach, where a worker is guided by laser projected outlines to place the workpiece. This provides for a quick setup and a prior on workpiece position within an uncertainty characteristic of manual placement. To observe actual position of the workpiece, we collect point cloud data of the workspace through a laser displacement sensor mounted on the robot. This is used to estimate the actual position of a workpiece with respect to

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the robot by calculating a transformation for the CAD model of the workpiece that best explains observed data.

Our system consists of two main modules; one for guiding the worker in initial placement and the other for estimating actual position of the workpiece. Though we have focused on welding as the manufacturing application, other operations could be executed by the robot since the workpiece position is now precisely known.

The remainder of this paper is structured as follows: Section II compares our efforts to current work, Section III deals with the configuration of our system, Section IV describes the localization module of our system and Sections V and V1 discuss the results and future work.

## II.RELATED WORK

The potential and need for smarter robots capable of adapting to its environment was discussed previously by [2] [4]. They proposed that CAD data of the workpiece be compared to real world workpiece data obtained through relevant sensors to estimate the position of the workpiece. Since then, most work [3], [5], [6] has been focused, using similar principles, in the computer numerical control (CNC) industry for workpiece localization. The objective in this case is to automate localization of workpieces fixtured onto the CNC machines. These approaches reduce the manual setup time required to perform manufacturing operations in the CNC machines. However, workpiece localization within CNC machines deal with constrained environments where the scale of the workpiece is well within that of the machine itself. Methods of observing geometric data and constraints of initial fixturing are limited to those scenarios alone. Work in the area of automating the process of welding in particular [7], [8] deals with identifying the seams in the workpiece alone and cannot be applied for other manufacturing applications. We are interested in design of a system that can be used for any manufacturing process with welding being our demonstration application

Recently, several methods have been developed to localize objects using CAD data in the field of humanoid robotics to interact with everyday objects [9], [10]. The objectives here too are quite different from our own. The time for localization and the final accuracy in the position of the object are less demanding here than in an industrial setting. A system proposed for an industrial setting should be comparable in performance to manual labor to be practical.

Our objective is to design a system capable of acquiring and processing data quickly to make a decision on the position of the workpiece. Here, we restrict the scope to localizing flat members in 2D space for localization.

## II. SYSTEM CONFIGURATION

All information required to execute the task - CAD models, members of the workpiece, list of workpieces, etc. is received by the workstation computer. This computer is directly connected to the following components.

*6-DOF robot:* We use an ABB IRB-2600 robot for enabling workpiece placement, inspection of the task post placement and for executing the welds. Its end effector is augmented with a GMAW torch, a laser projector and a laser displacement sensor (Fig. 1)

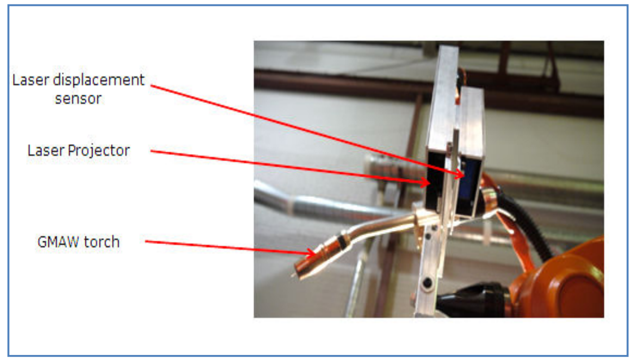


Figure 1. Robot end-effector augmented with a laser projector and a laser displacement sensor.

*Laser Projector:* A Microvision ShowWX+ laser projector is attached to the end effector of the robot to guide the worker for quick workpiece placement.

*Laser Displacement Sensor*: A Micro-Epsilon 1402-1200 laser displacement sensor (laser sensor) is also mounted on the end effector of the robot for workspace inspection. It has a displacement (depth) accuracy of 0.288mm (assuming flat, rigid and non-reflective surface). This sensor acquires data from workspace for localization. Fig. 2 represents a point cloud obtained after a spiral inspection of the workspace holding a member of an automobile spaceframe Fig. 3.

The accuracy of any point observed by the robot–laser sensor coupling is within a region of 0.4mm confirmed by experimental results on gauge surfaces. Both the laser sensor and the laser projector are calibrated so that all data, input and output, is with respect to robot reference frame $C_R$.

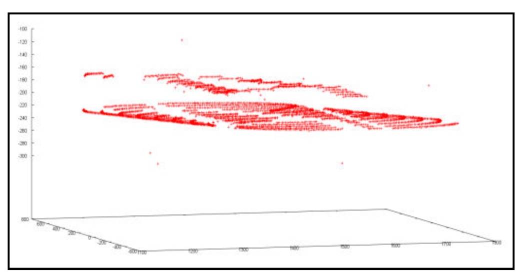

Figure 2. Point cloud obtained after scanning workpiece in Fig. 3

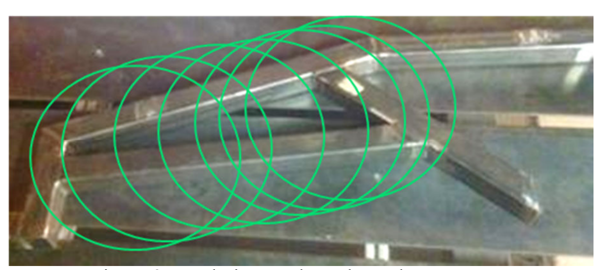

Figure 3. Workpiece and overlapped scan pattern

## III. PROPOSED APPROACH

The process flow diagram (Fig. 4) shows the steps involved in our system. Each of these steps is discussed in detail in the following sections.

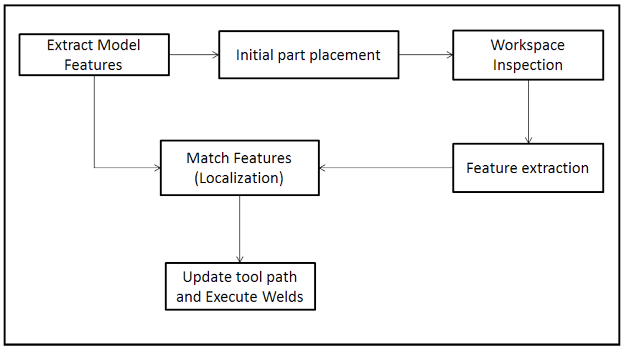


Figure 4. Process flow of our system

### A. Model feature extraction

Features identifiable from observed laser sensor data need to be extracted from the CAD models to be matched for localization. Since the laser sensor produces topography of the surface observed, edges (drop-offs) are the most prominent features that can be identified. To match this feature, we extract the edges from the CAD models to create a 2D template of the workpiece (Fig. 5). Each member is described as a group of line segments (boundary) and each line segment is represented by a pair of points. So a template having 6 quadrilateral members is represented by 24 line segments forming the outline of the workpiece.

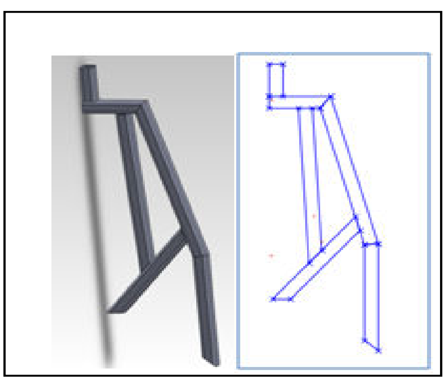

Figure 5. Representation of workpiece CAD model (left) as a 2D template (right)

### B. Initial workpiece placement

For quick initial fixturing, cylindrical magnets are used as fixtures to constrain the members along their axis. The position of the workpiece within the workspace is pre-planned based on the envelope of the reach of the robot. Each workpiece is tagged with a number for ease of identification. In our experiments, we centered the entire workpiece within the working envelope of the robot. This envelope is calculated from the joint limitations of the robot. The position of each member of the workpiece and the position of the cylindrical fixture on the outer boundary of each member is successively calculated. These positions are then highlighted by the mounted laser projector for the human worker to place the fixtures (Fig.6).

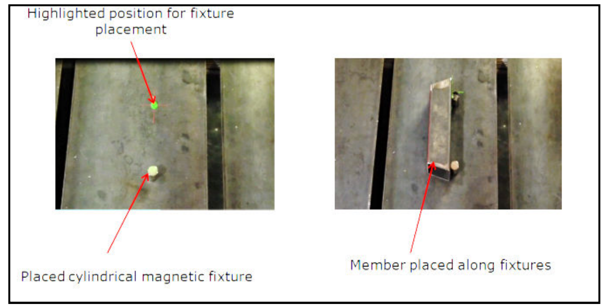


Figure 6. Fixture position highlighted by robot mounted laser projector (left) and workpiece placement (right)

### C. Workspace Inspection

The inspection procedure obtains information of the workspace through the laser sensor. As we are interested in the edges of the workpiece, the objective of the inspection is to cut across the major axis of the members. The inspection pattern is to be designed as a workpiece search procedure spanning an envelope around the planned position. We have designed two such inspection plans to observe the workpiece. Either plan can be chosen as an option, based on workpiece geometry, while executing the inspection command.

*Local Inspection* - This method focuses on inspecting individual parts of the weldments. This was designed so that we can sample points equally from each member. The pattern resembles a zigzag across the major axis of each member (Fig 7). Pattern position of each member is calculated from its planned position. The span and frequency of sampling is provided as inputs while calling the program. Larger span and frequency would be required, at the cost of time, when large error in initial placement is expected. This pattern is recommended when the members of the workpiece lie predominantly along the boundary of its convex hull. This is usually the case when the workpiece consists mostly of butt-joints. One issue faced by this method is the vibration from heavy acceleration in the robot motion at the extremes of the zigzag pattern, causing noisy data acquisition.

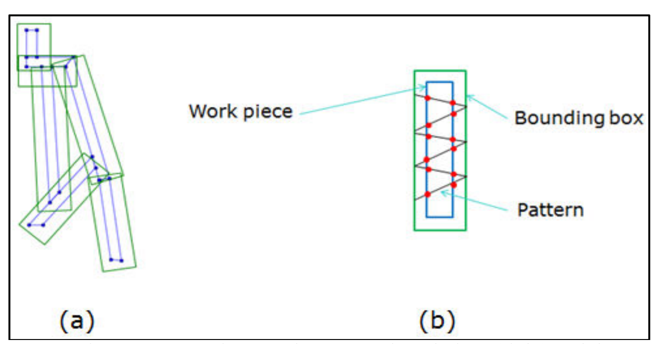


Figure 7. Inspection envelope around workpiece (right) and the inspection pattern within each envelope (left) for local inspection. Red dots represent observable edge features.

*Global Inspection* - The pattern resembles a spiral shape to avoid sharp changes in acceleration (Fig. 8). This method focuses on inspecting the workpiece as a whole, recommended when there are members present within the interior of the convex hull of the workpiece. A zigzag pattern applied here would result in redundant inspection moves to neighbors that could have been included in a single pass. This case is usually seen when a workpiece holds many miter-joints. As this inspection is to happen across the entire workpiece, the major and minor axis of the entire workpiece is calculated from their eigenvectors. The inspection is done along this axis.

One of the disadvantages of this procedure is that we have no control over the sampling density of the individual members of the workpiece. Excessive sampling of a single member adds more weight to fit the points along its edges when optimizing.

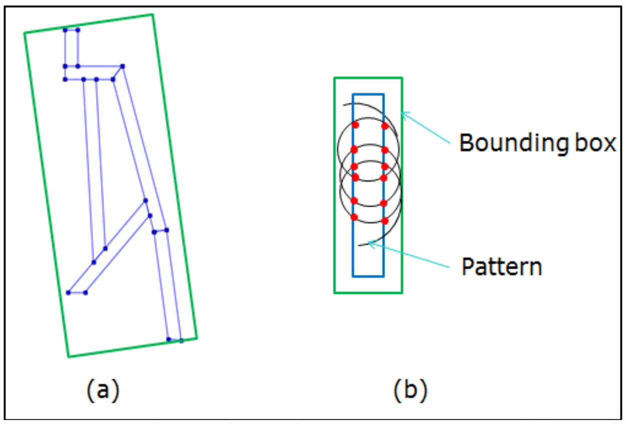


Figure 8. Inspection envelope (left) and inspection pattern within envelope (right) for global inspection. Red dots represent observable edge features

*D. Feature Extraction*

Laser sensor data (1-dimensional with only depth, Z) from the inspection plan is synchronized with robot motion (X, Y) to obtain the X, Y, Z values of the inspected surface over time. As edges carry most information (Fig. 7, 8, 9), the objective is to extract them as features from the point-cloud data. As there is a sharp change in the Z value (drop off) along the edge, this feature is used to identify those points (Fig. 9). The edge extraction procedure follows methods similar to the edge detection algorithms used in computer vision. We apply a two stage convolution (to filter noise) with step kernels (-1, 1), analogous to calculating a differential, to identify the points along an edge. Surface height information from the CAD model is used as thresholds to eliminate noise. Points along the top and bottom of an edge are averaged to represent a slot like formation into which we expect the actual edge to lie. Thresholds of 0.6mm as the maximum gap (on the XY plane) of the slots are applied to maintain a tight fit of the edge. We average the X, Y positions of the points lying on either side of an edge to localize the edge between them as the point lying precisely on the edge cannot be read out from the laser sensor due to shearing.

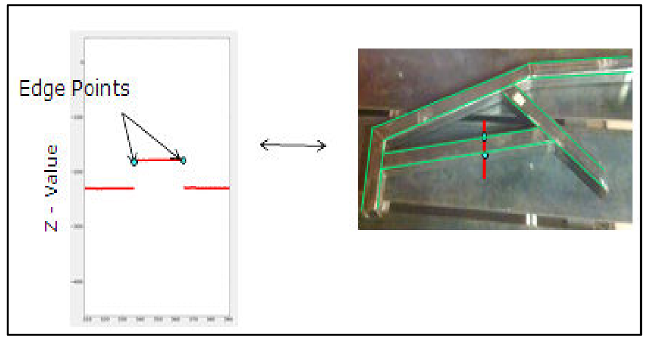


Figure 9 Edge points observed, (left) from a single linear scan across the workpiece (right)

IV. LOCALIZATION

Since we expedited the placement of the workpiece through a human worker, an error between the planned and actual position of the workpiece is introduced. To recover the actual position of the task on the workspace, we require a 4x4 homogeneous transformation matrix $M$ (1) that represents the offset or translation $T$ in X, Y and rotation $R$ in Θ of the workpiece from its planned position $P_{Planned}$ to its estimated position $P_{Estimate}$, (2) representing the actual position of the task after placement, in reference frame $C_R$.

$$M = [R] * [T] \tag{2}$$

$$P_{Estimate} = M * P_{Planned} \tag{3}$$

Ignoring symmetry, this transformation, $M$, must be unique to get a valid solution for (2). For any given member, we require at least 2 points along each edge (of the major axis) to constrain it along the major axis. This allows for sliding (or multiple solutions) but similar points on neighboring members constrain this freedom providing for a unique $M$ to explain the observed data (Fig. 10).The denser the points on each edge the more confidence there is in a particular fit.

The edge extraction process provides data required to calculate such a transformation. In our system we assume that the workpiece has been sampled dense enough to meet the above requirements.

The objective is then to rotate (Θ) and move the template (X, Y) from its planned position to cover the extracted edges as much as possible. The parameters to optimize over are X, Y and Θ representing the translation and rotation of the workpiece from its planned position on the XY plane (workspace).

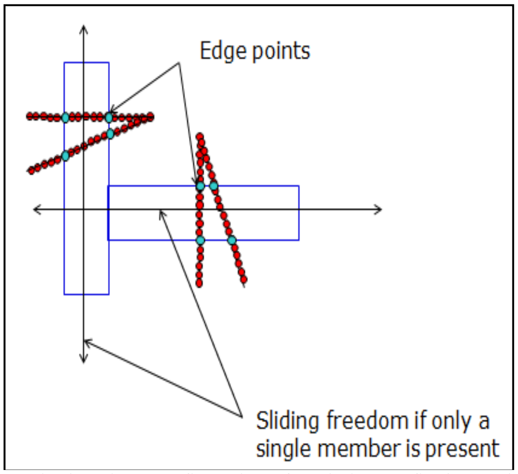


Figure 10. Single unique configuration of workpiece to fit observed data (green and red)

The algorithm to minimize error (over X, Y, Θ) to get the best fit is based on the iterative closest point algorithm designed as follows:

- Calculate the shortest Euclidean distances *D,* between each of the edge-points and each of the template line segments.
- For each edge point the distance to the closest line segment represents its error.
- The total error for any position of the template is the sum of all edge-point errors.
- Update position of the template (through X, Y, Θ) to reduce current error. Update current error
- Repeat until current error does not reduce

For any given template $P$ holding $k$ line segments $l_i, l_2, \ldots l_k$ and observed set, $S_n$ of ponts $s_1, s_2, \ldots, s_n$ points the fit error $E_{FIT}$ is given by (3)

$$E_{FIT}(S_n, P_k) = \sum_i^n argmin_{j \in \{1,\ldots k\}}(D(s_i, l_j)) \quad (3)$$

Where, as mentioned before, $D$ ($s_i$, $l_j$) represents the shortest Euclidean distance between a point $s_i$ and a line segment $l_j$..

*Optimization*

Once we have the objective function and data, we need to optimize iteratively over X, Y, Θ to find the best fit. Our optimization problem is a non-convex one where an analytical gradient cannot be calculated. A search based iterative method to reduce fit error $E_{FIT}$ at every step is one way to solve this problem. The optimization problem is given by -

$$\underset{X,Y,\Theta}{\text{minimize}} \; E_{FIT}(S, \; M_{X,Y,\Theta} * P) \quad (4)$$

where $S$ represents the set of observed edge points, $P$ represents the set of line segments defining the template and $M_{X,Y,\Theta}$ is the transformation matrix to be found. We employ Powell's method to search for local minimum using conjugate gradients.

The chance of arriving at global minima with Powell's method is dependent on the initial seed point. Searching from multiple seed points increases the chance of finding the global minimum. The seeds are generated within a neighborhood of 50 mm in X, Y and ± 20 degrees rotation from center of mass and orientation of the extracted edges respectively. Since our setup has eight separate processor cores, we can run 7 optimizations in parallel (without higher cost) with the different seed points. We pick the result that has the lowest error among all 7 as the final result. Localizations where optimization yields a result with an average error of over 2.5mm (empirical) are considered as failures since this is beyond the tolerance limit for welding.

The output of the optimization gives X, Y and Θ that represent the transformation to be applied. This data is used to get the transformation matrix $M$ (3) and a guess at actual position of a workpiece is obtained from (4). Fig. 11 shows the result after localization on a workpiece. Once the transformation $M$ is obtained, it can be applied on the weld positions (extracted from the CAD model) to re-calculate the weld path of the robot.

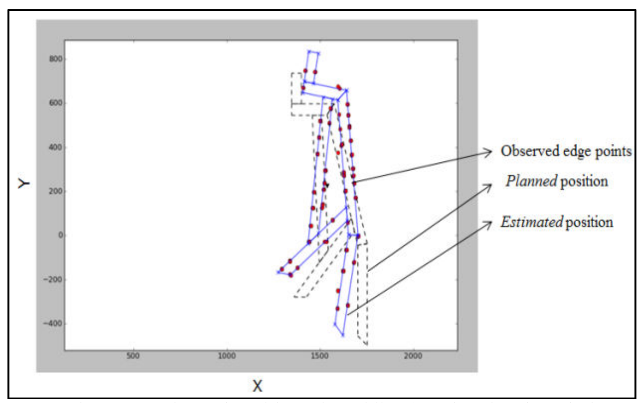


Figure 11. Planned position (dotted lines) and updated workpiece position (blue lines) based on observed data (red dots)

## V. RESULTS

Welds were localized on workpieces (Fig. 12) with an induced initial placement error of ±15mm offset and ± 20 degrees rotation. The final estimated position of the welds in each of the templates was compared to the ground truth. Table 1 shows the results of the comparison.

Table 1. .Localization variance over 150 trials

| **Standard deviation over X (mm)** | **Standard deviation over Y (mm)** | **Standard deviation over Θ (degrees)** |
|---|---|---|
| 0.31 | 0.43 | 0.36 |

The system was able to localize workpieces placed roughly by a human to approximately the same accuracy as the input point cloud. Variation of workpiece geometry from CAD model was not addressed and was the primary cause of weld localization failure, which was under 13% in trials. In such cases a message is sent to perform the weld manually.

## VI. CONCLUSION

The workflow of quick and rough but guided human placement followed by fine localization and robotic operations was quite effective. We have avoided single part fixtures, instead moved CAD information to the fabrication floor to be used for automated instruction and localization. Tests were conducted on flat workpieces (Fig. 12) for evaluation. Times for the same task reported by Pratt & Miller Inc., using best industrial practices, were used as the base line for comparison. In collaboration with Pratt & Miller our system was able to produce time savings of over 85%.

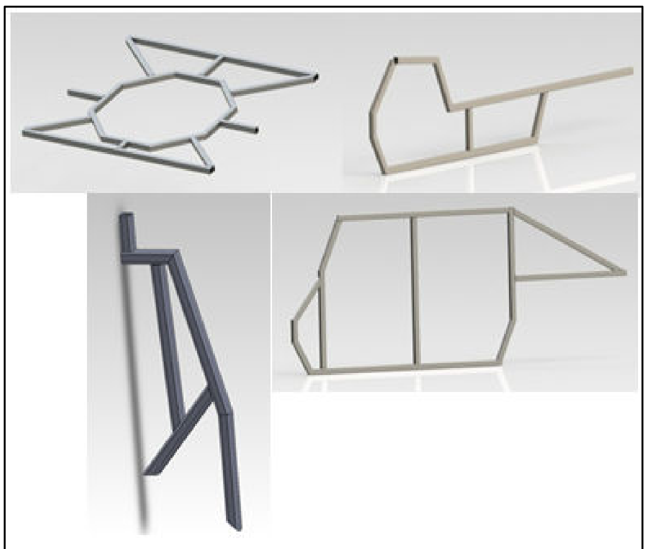

Figure 12.Workpieces used for testing

The system we implemented is restricted to fabrication of flat weldments consisting of straight tubular sections. We are working to generalize our logic and fixture strategy to work on generic 3D welded assemblies, and to better address tolerance variation in input materials.

## ACKNOWLEDGMENTS

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