Seam Tracking with Adaptive Image Capture for Fine-tuning of a High Power Laser Welding Process

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ABSTRACT

This paper presents the development of methods for real-time fine-tuning of a high power laser welding process of thick steel by using a compact smart camera system. When performing welding in butt-joint configuration, the laser beam's location needs to be adjusted exactly according to the seam line in order to allow the injected energy to be absorbed uniformly into both steel sheets. In this paper, on-line extraction of seam parameters is targeted by taking advantage of a combination of dynamic image intensity compression, image segmentation with a focal-plane processor ASIC, and Hough transform on an associated FPGA. Additional filtering of Hough line candidates based on temporal windowing is further applied to reduce unrealistic frame-to-frame tracking variations. The proposed methods are implemented in Matlab by using image data captured with adaptive integration time. The simulations are performed in a hardware oriented way to allow real-time implementation of the algorithms on the smart camera system.

Keywords: Laser welding, Thick steel, Seam tracking, Hough transform, Smart camera

1. INTRODUCTION AND RELATED WORK

Although the path of a robot guiding a laser welding head can be pre-programmed, fine-tuning of the laser beam to the exact seam location is essential to allow the injected energy to distribute evenly to both metal sheets. This requires on-line inspection of the seam position and real-time automated control of the welding robot. The high variation in intensity dynamics within the visible spectrum in laser welding is challenging for automated vision algorithms, which have to cope with visual noise, lack of detail in poorly illuminated areas and saturation in highly illuminated areas. Various methods have been proposed to tackle these problems for the implementation of visual weld seam tracking. Stereo or structured light imaging [1, 2] can be used to extract the 3D geometry of a weld seam. However, very small seams widths in the laser welding process can be indistinguishable from the flat metal surface, which is why analysis based on direct visual imaging has also been actively developed. In [3] the shape of the weld pool, which consists of the melt surrounding the laser beam, was captured visually with a 2D camera and used to determine the parameters of the weld. In [4], thermal radiation in the near-infrared spectrum was used to assist the determination of the seam and weld pool properties with a high-speed camera, and the authors in [5] proposed shuttering the camera in pulsed Nd:YAG welding in accordance to the instant changes of the laser pulses affecting the image intensity dynamics. Recently, in [6] a Kalman filter and a neural network was proposed for improving the seam tracking accuracy of a laser welding process based on 2D visual analysis. In [7], Hough transform in combination with limiting the accumulator space into specific interval was proposed for the tracking of the welding seam. However, the focus of that paper was to study how efficient pre-filtering of the Hough transform could be implemented.

In [8], a smart camera was used to control the laser power in the welding process by monitoring the keyhole dynamics, resulting in improved welding quality. In this paper, we examine the application of a similar smart camera system for visual seam tracking, with a goal to enable real-time fine-tuning of the robot path in laser welding of thick steel sheets. The problem of large inter-scene illumination variation is in our case handled by the high-speed smart camera, which performs real-time dynamic compression by adapting the local pixel integration times according to the estimated average regional intensity [9]. This allows the observation of the darker plate seam even with the high intensity weld-pool in the same scene. Also, image preprocessing and segmentation and Hough transform based line detection and line tracking can be implemented directly within a single embedded smart camera device. Performing all of the necessary image analysis on the camera- and even on the sensor-level allows the implementation of a very high speed and *small delay* monitoring and control-loop for the welding system within a very compact platform.

In this study the KOVA1 camera [10], which consists of a 96x96 sized CMOS sensor chip with processor-per-pixel functionality and an FPGA co-processor was used for capturing the welding footage as a baseline for the algorithm development. In previous research [11] an FPGA-based implementation of the Hough transform on the KOVA1 camera platform was demonstrated. In this paper, the seam-tracking analysis implementation is examined in a simulated environment in Matlab, however, real image data captured from laser welding tests with the smart camera was used as input. Hardware-realistic simulations are used for the development of the system, i.e. by using only operations which can be actually implemented with similar accuracy within the actual embedded camera platform. The results will give an indication on the feasibility of the proposed approach for real-time seam tracking and will be applied in further practical testing with on-line processing.

2. PIXEL-PARALLEL IMAGE SEGMENTATION AND LINE FILTERING

2.1 Pixel-parallel image segmentation

In the targeted monitoring system the input images are segmented to reduce redundant information while preserving the seam features. The segmented black-and-white (BW, 1b) images are then applied to a Hough transform and additional higher level spatial and temporal analysis to extract the seam location and direction. In the Matlab simulations used for the off-line development reported here, constraints created by the embedded hardware e.g. on the accessible pixel neighborhood, have been taken into account and only processing operations supported by the camera hardware were used. The input data used in the simulations was captured with the KOVA1 camera in earlier laser welding tests, by using real time image intensity compression. Image segmentation can be performed within the KOVA1 smart camera with pixel-level analog processing circuitry based on current-mode computation and local (dynamic) current memories, within a locally connected pixel-processor network [9, 10].

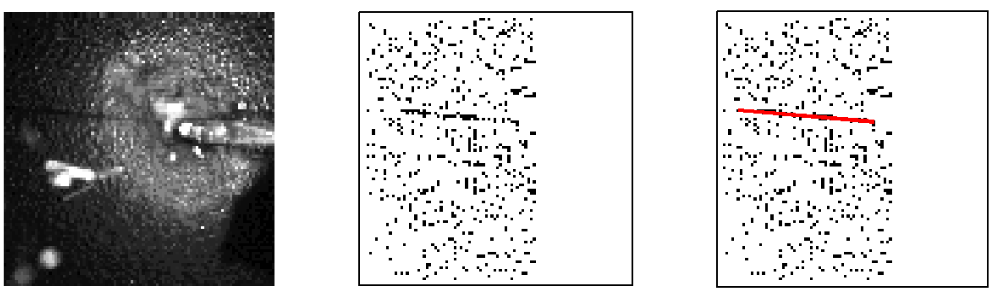

Figure 1. Left: Original image captured with only radiated illumination from the laser interaction area, using on-chip dynamic compression on the smart camera. The image scale is approximately 0.2mm/pixel. The seam is mostly visible to human eye and the melt pool extends the right from the bright laser interaction area. Middle: Segmented B/W image (Matlab), where the right-hand side of the image has been logically masked. Right: The dominant line candidate extracted by the Hough transform (Matlab).

As can be seen from left side image of Fig. 1, the seam is visible as a thin dark line in the captured camera images. From the camera setup it is also known that the seam lies approximately in horizontal direction in the camera view. The segmentation algorithm was therefore optimized to extract thin dark features with a dominantly horizontal orientation. In KOVA1 both local 1st and 2nd pixel neighborhoods can be accessed directly in image operations by each pixel-processor cell, depending on the type of processing operation. In this case each pixel value is processed in its second order neighborhood by comparing the intensity value of the center pixel I_L=I(cx,cy) to its neighbors in directions I_{NW}=I(cx-1, cy+2), I_{NE}=I(cx+1, cy+2), I_{SW}=I(cx-1, cy-2) and I_{SE}=I(cx+1, cy-2).

The intensity value of the center pixel is sequentially compared against the pixel value of each selected local neighbor and at the same time the absolute value of the difference between the neighborhood pixel and the local pixel is extracted. If the neighboring pixel has a larger value than the local pixel and the difference between the pixel values is larger than a programmable threshold value, the value for the local binary memory B_{XX} for the examined direction is set to a logical 1. The final segmentation result is achieved by combining the separate direction results with pixel-level logic circuitry, so that B_L=AND(AND(B_{NW},B_{NE}),AND(B_{SW},B_{SE})).

The input data used in Matlab also contains any inaccuracies and dynamic losses introduced by the on-chip A/D conversion (6-bit grayscale output data) used for video capture. In reality the on-chip processing is performed prior to A/D conversion, i.e. on the direct analog pixel values without ADC-related variation. On the other hand, the pixel-level analog processing on the KOVA1 is also affected by inaccuracy, noise and nonlinearity, which cannot be easily modeled in Matlab. As can be seen from Fig. 1, the segmented images applied to the Hough transform are allowed to be very noisy, as long as the real seam-related features dominate the image statistics. The sensitivity and amount of noise in the segmentation can be controlled on the KOVA1 with the absolute value operation threshold and other on-chip biasing.

The middle image in Fig. 1 shows the result of the segmentation operation computed in Matlab. The area behind the keyhole was masked from the segmented image, because the plate seam is not visible in the melt pool area. Also, since the FPGA execution time per frame of the Hough transform is dependent on the number of "1" bits in the segmented binary image [11], reducing redundant information as much as possible helps to guarantee high frame-rate on-line operation. However, at the beginning of the weld, it might still be reasonable to also take the area behind the keyhole into consideration. Additional masking, e.g. of the top and bottom parts of the image, could also be implemented; such logical mask operations can be performed in a pixel-parallel fashion on the KOVA1 sensor plane.

2.2 Extracting the location of the laser beam

Since the camera is fixed to the welding head in a co-axial configuration, the position of the laser beam within the camera view remains at the same location during the welding sequence, however, the automatic determination of this position makes it easier to manage possible inaccuracies in the mounting of the camera. During the weld monitoring operation, the camera is operated in a *triggering mode*, i.e. data is read out of the image sensor only when some predefined activity is detected within the camera view. In this case the applied triggering condition was sufficient visual intensity in some part of the imaging area, in practice in the laser interaction area. Because the trigger operation is processed on the sensor plane, the onset of the laser beam can be captured very quickly at the beginning of the welding, before the actual weld pool or any spatters have formed, allowing the laser beam location to be determined.

The location of the laser position can be determined with the pixel-level processing circuitry and used as input to the FPGA. The FPGA then uses this information when calculating the distance between the laser beam and the seam line. Since a simple threshold operation is used to determine the triggering condition, the threshold result for the first frame(s) can be stored into a local binary memory and used to indicate the location of the laser beam for the subsequent Hough operations. In the performed simulations taking a bitwise AND operation between succeeding images of the first five frames, resulted in correct laser position initialization; the same logical operation can also be implemented with on-chip processing.

2.3 Description of the tracking algorithm

The seam tracking algorithm is illustrated in Fig. 2. The input is a stream of B/W images which have been segmented in Matlab from a grayscale video captured earlier with the KOVA1 camera. Line extraction with the Hough transform is implemented in Matlab with realistically selected accumulator resolution. The significant parameters for the Hough transform are ρ, which is the distance of the line from the origin at the upper left corner and θ, which is the angle of the line, between -90° and +89°. These are both varied with a step of 1 in order to keep the simulation realistic with respect to the actual FPGA implementation. Two 1-dimensional histograms, for ρ and θ, within a fixed temporal window of N=1-100 frames are generated to utilize temporal correlation between detected line candidates. A new line candidate is accepted only if the distance between the predetermined location of the laser beam and the proposed line is sufficiently small. This is based on the assumption that the uncorrected error in the position of the welding robot with respect to the actual seam location is below some reasonable threshold. A threshold value of $Th1$ < 5 pixels was selected for the simulations (see Fig. 2).

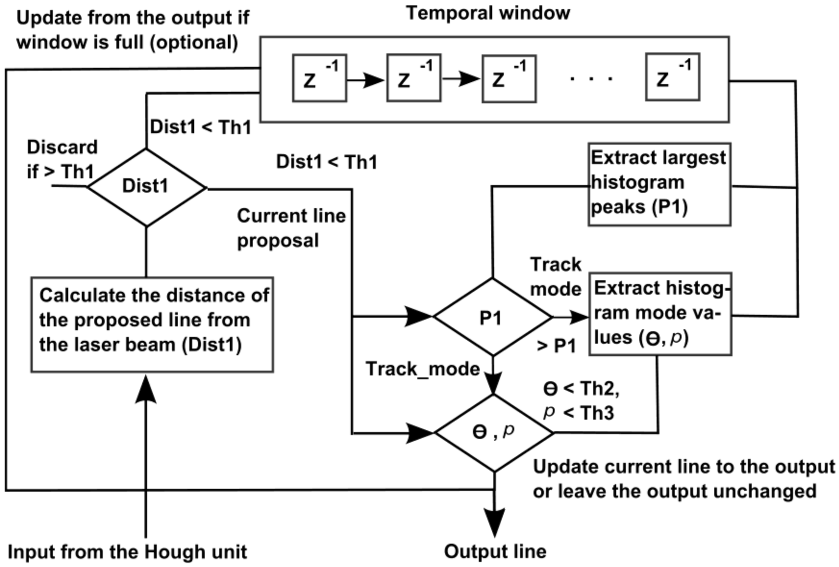

Figure 2. A flow diagram of the tracking algorithm. The inputs are line candidates from the Hough unit, which locate on the FPGA chip. If the number of correct line candidates is above some pre-defined threshold within the temporal window, the system enters into tracking mode. After entering into tracking mode, the change in the line orientation and location is assumed to be smooth.

When first N line candidates have been obtained the system can conditionally enter into a tracking mode. The tracking mode is enabled if the sum of *P* dominant peaks (here P=4) in the temporal histogram window is above a set percentage threshold. The tracking mode is again disabled, if the sum of *P* dominant peaks falls below the threshold value (see Fig. 2). When the system is in the tracking mode, the highest peak (*mode*) within in the temporal window is determined. A new line candidate is then accepted as the output only if the change in ρ and θ is sufficiently small (that is, $\Delta\theta < Th2$ and $\Delta\rho < Th3$, with respect to the *mode* value). If the system is in the tracking mode, and the input line candidate does not fill the threshold criteria of the temporal window, the output is left unchanged until a line candidate fulfilling the criteria is found.

3. ALGORITHM EVALUATION

The welding system used to acquire the test data consists of a 10kW laser with the welding head attached to a robot arm. The camera was attached to the welding head in a coaxial configuration. The test data consists of four image sequences captured by the KOVA1 camera. Prepared and purified 9mm thick S355 structure steel sheets were welded together in a butt-joint configuration. The focal position of the laser beam was 6mm below the surface in each of the test sets. The laser power varied from 10kW to 6kW, welding speed was 2-2.5 m/min and the image frame difference was 1.6ms for the first test sequence and 2ms for the three other sequences.

The seam was located roughly in the same position and orientation with θ_0= -84° in each of the test sequences, i.e. this was considered as the ground truth for the algorithm evaluations. An example of filtered and non-filtered θ histograms from *Sequence 2* is shown in Fig. 3. In can be observed, that the filtering reinforces the peak at -84°, while effectively removing the false line candidates resulting from noise. The high spikes corresponding to ± 45° angles in the non-filtered data are a result of an artifact from the segmentation process, which can frequently create 3-pixel local clusters in a right angle configuration. If the actual seam is not visible in the frame, these artefacts can dominate among otherwise random data, leading to a preference of 45° line candidates. It should be noted that the non-filtered data shows the best Hough line candidate within each image frame, without any discrimination on the actual quality, robustness or location of the extracted line in particular.

The robustness of the tracking was examined by comparing the raw Hough transform results to the filtered data, and by calculating the percentage of extracted lines from the whole sequence, which were within a small interval from the determined ground truth, i.e. $\theta_0 \pm 2°$. From Table I and by examining the welding videos visually, it can be observed that the generation of plume and spatters as well as illumination conditions decreased the recognition rate. Without filtering the matching rate in the four test sequences was in the range of 9.1% - 77.6%, while filtering improved this to 82.4% - 98.7%.

To test the adaptation of the histogram window method to gradual changes in the seam orientation and location the test videos were manipulated so that a cumulative rotation of 0.01-0.02°/frame was applied to the image data. A maximum inclination of 40° was thus achieved across the approximately 2000 frame test sequences. In order to measure the distance between the seam and the laser beam location similarly as without rotation, a virtual location of the laser beam was mapped to the location given by the same rotation transformation. In Fig. 4, the distance between the laser beam location and the extracted seam line is plotted for the non-rotated and rotated sequences, respectively. A temporal window size of N=50 was used. It can be observed, that in this case the behavior of the rotated and non-rotated output signals correspond well to each other. With some additional 1D filtering of the temporal data, the tracking noise could be further reduced.

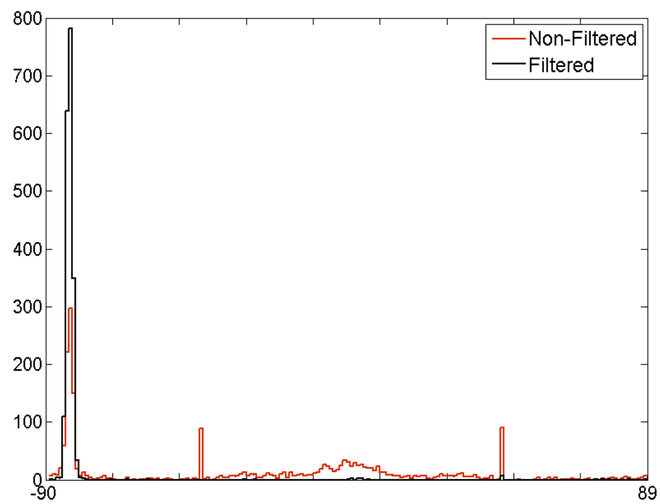

Figure 3. The distribution of the θ values for a normal and a filtered sequence. It was required that the distance from the seam line to the position of the laser was less than 5 pixels and that θ and ρ parameter values were within 2° or 2 pixels, respectively, from those of the dominant peak. The tracking was initiated only if the volume of four largest peaks in the θ histogram was above 35% and the corresponding volume of the ρ histogram above 20%. Sequence 2 was used with a window size of 50.

	Sequence 1	Sequence 2	Sequence 3	Sequence 4	Average
Non-filtered	0.225	0.382	0.091	0.776	0.369
Filtered (window size = 50)	0.929	0.980	0.824	0.987	0.930
Filtered (window size = 10)	0.757	0.979	0.826	0.987	0.887
Filtered (window size = 1)	0.831	0.975	0.740	0.984	0.883
Non-filtered, rotated 0.01 degree / frame	0.146	0.252	0.056	0.655	0.277
Filtered (window size = 10), rotated 0.01 degree /frame	0.830	0.902	0.579	0.928	0.810
Non-filtered, rotated 0.02 degree / frame	0.122	0.179	0.038	0.574	0.228
Filtered (window size = 1), rotated 0.02 degree /frame	0.656	0.610	0.187	0.928	0.595

Table I. Correct line detection rates in the normal and filtered operation modes. The average number of active pixels generated by the segmentation within all test sequences was ~560, thus enabling Hough analysis at a frame rate slightly below 400 fps on FPGA [11], i.e. with a ~2.5ms frame difference. Additional frame-rate improvement could be achieved by further limiting the seam search area below and above the keyhole.

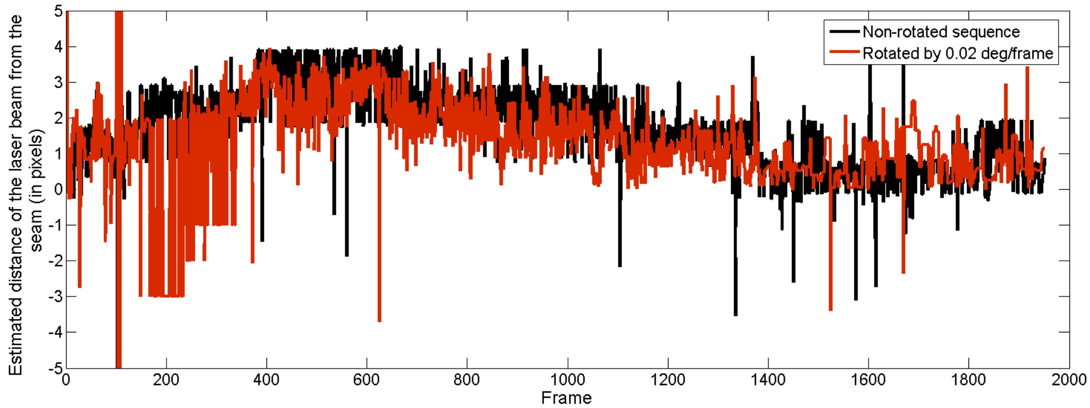

Figure 4, The estimated distance (in pixels) of the seam line from the laser beam. The inclined sequence was captured with cumulative rotation of 0.02°/frame. Sequence 4 was used with window size of 50. This figure represents the best results achieved, when the spatter and plume generation was the smallest. The parameters for line filtering were the same as in Fig. 3.

3.1 Performance estimation

The performance of the overall visual analysis system is expected to be affected by three factors. First, the time used in the segmentation step implemented on the camera sensor plane, second, the time required by the FPGA-based Hough unit for detecting the new line candidates and third, the time consumed for the temporal line filtering method. Because the B/W segmentation is performed in a fully pixel-parallel fashion and in also parallel to the Hough transform, it is expected to very fast, enabling processing rates of tens of kFr/s. The tracking algorithm is also expected to be very fast as long as the temporal window sizes remain reasonable. The Hough transform computation on the FPGA is expected to be the main bottleneck of the system in terms of processing delay. In an earlier research, frame-rates between 234 fps (1000 “1” pixels in the segmented binary image) and 1000 fps (50 ”1” pixels) were tested in practice on the KOVA1 camera FPGA co-processor [11]. Further improvement to this could be gained by limiting the Hough accumulator space into only specific intervals, assuming that the seam orientation and location is not arbitrary [7].

4. CONCLUSIONS

The paper studied embedded image processing methods for the implementation of on-line monitoring and control of the position of the laser beam in high power laser welding of thick steel. Seam tracking in the welding of thick steel is challenging due to noise, lack of detail in poorly illuminated areas and saturation of the intensities in highly illuminated areas. Real-time control of a welding robot requires a very high speed analysis platform. The approach of this paper was based on embedded camera-level processing with sensor-level preprocessing and segmentation. The following processing steps analyzed were Hough line detection and temporal filtering which can be mapped on the FPGA. The proposed algorithms were tested in Matlab with real laser welding image data, in order to facilitate further on-line testing and taking into account the hardware-level capabilities of the embedded processing platform. The proposed temporal line filtering method improved the original Hough line detection rates in all test sequences and even despite of artificial image rotation. A major challenge in the line filtering was that most of the initial line candidates were not valid. This issue was confronted in this paper by assuming that the correct line candidates still dominate the ρ- and θ -histograms of all the line candidates. With the test data captured this assumption could be held valid. Additional 1-d filtering, which can also be implemented on the FPGA, could be further applied to the output signal. When all of the processing is performed within an embedded camera platform, any communication delays present e.g. in a camera-PC/DSP system are removed and the control signals for the robot system can be provided with minimal lag.

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