Image Processing Technology and Deep Learning Application: In Relation to the Context of Laser Positioning

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Abstract-- In the current investigation, there was the use of the technology of machine vision. The usage of this technology was informed by the need to have the laser spot’s highest energy positioned precisely, eventually allowing for the facilitation of further product work piece joining. Indeed, the joining occurred in laser welding machinery. Relative to the displacement phase, it is notable that it could aid in work piece placement into superposition areas, upon which there could be the joining of the parts. Training programs or models that were used involved convolutional neural network and deep learning, which allowed for the resultant system’s enhancement of the accuracy with which the positioning could be achieved. Also, the aforementioned algorithms were insightful because they led to the enhancement of machine work efficiency. Similarly, in the study, there was the proposing of a bi-analytic deep learning localization technique. For the purpose of system monitoring in real time, there was the use of a camera. As such, the initial stage entailed the application of the convolutional neural network, which aided in the implementation of large-scale initial searches before having the laser light spot zone located. In turn, the phase that followed entailed increasing the camera’s optical magnification, which paved the way for the spot area’s re-imaging, as well as the application of a template matching method to ensure that high-precision repositioning was achieved. For the case of the complete laser spot, there was the performance of the centroid calculation. Also, in situations where an incomplete laser spot reflected the target, there was the performance of invariant moments’ operation. From the findings, the study indicated that from incomplete laser spot images, the laser spot’s highest energy could be positioned precisely. The study also established that in order to establish the displacement amount, the image’s center and the laser spot’s highest energy could be overlapped.

Keywords-- Convolutional neural network, deep learning, laser spot, machine vision.

1. INTRODUCTION

With a quick evolution in science and technology, there is a continuous decrease or reduction in material sizes or the Size of various parts of systems. To have the resultant miniature parts combined successfully, therefore, there is a growing need for the highest precision possible, a demand proving higher when compared the precision required when dealing with general parts [1, 2]. Also, while dealing with the miniature parts, especially in the context of mass system production, there is fixed production time for the respective parts [3]. Hence, in case of laser radiation offset that causes the junction’s soldier to fail to have adequate energy absorbed, there might be failure in the weld [4]. Similarly, given some part, should the laser’s high-energy zone irradiate other positions, there could be a direct rejection of the given
part [5]. The eventuality is that for the laser, there arises a need to have the highest energy zone searched and positioned [6].

For the majority of previous scholarly studies, the focus has been on the implementation of various hand-craft features. This usage has been informed by a quest towards representing the images’ visual content, as well as the establishment of relevant measurements of similarity, achieving a similarity of low-level features and also ensuring that it (the similarity) is closer to that of high-level concepts [7]. When it comes to the deep convolutional learning technique, most studies document that it has steered improvements in the ability of feature extraction, implying that its implementation fosters efficiency when it comes to the measurement of similarity [7, 8]. In these studies, given a sample image, there was the extraction of its feature training classifier. Here, the neural network was used, a process that preceded the matching criterion. The eventuality is that there was the establishment of the input image’s laser spot. There was also the searching of the center spot before moving the laser spot position to ensure that it overlapped the Charge-coupled Device (CCD) camera’s image center. This overlapping process sought to ensure that the positioning criterion was completed. Important to note is that in situations where there was the use of large ranges of images, for incomplete spots, their images would often appear. As such, even though there was the realization of the spot re-imaging procedure’s precise positioning, much time was consumed. Therefore, in the current investigation, the central purpose lay in the combination of a deep learning algorithm with machine vision. This combination sought to have a positioning system built, which could aid in the alignment of the center spot of the laser quickly and automatically.

When it comes to traditional techniques of template matching, it is worth remembering that they come with various defects. For instance, on each occasion that templates are changed, the techniques call for weight updating and continuous matching [9]. Important to highlight is that these defects waste a lot of time. Another problem with such techniques is that in situations where an area of the matched image and that of the template image are similar but they do not coincide with the target area, the resultant matching could be false [10]. Indeed, for imaging systems, they employ various parameters and databases. For the case of high-resolution images, they offer easy and precise position detections [11], yet, when it comes to contexts involving real-time systems, the computational costs associated with the high-resolution images are high [12]. To solve the recognition accuracy problem, some studies have proposed and advocated for the use of a hierarchical matching [13, 14], but these previously proposed schemes of classification do not come with all potential features. This failure is attributed to variability vastness regarding feature topology and geometry [15]. In this investigation, therefore, the main aim was to utilize or employ the deep learning technique for the purpose of enhancing feature recognition, as well as shortening the needed time for obtaining results. The motivation of the study was to remedy the aforementioned defects with which most of the previously proposed techniques have been associated.

2. METHODOLOGY

Notably, the purpose of template matching involves seeking parts of images that tend to match the given template image [3]. Initially, the read-in template images have their sizes and those of the matched images determined via calculation, with the outcomes stored. Should template images fail to divide exact the matched images, there is the supplementation of the bottom and right of the image by 0 [4]. In turn, there is the substitution of the image into a given model or algorithm. The role of this substitution process into the algorithm involves the determination of the template image’s weight for the respective points within the matched image. With the maximum weight established, the upper left corner’s position is determined relative to the matched image’s template image. The next step involves inputting the template image’s width and length. Given the matched image, then, there is the indication of the template image’s region [16]. While numerous algorithms characterize the method of template matching [17], the current study relied on the case of the Sum of Squared Differences (SSD). It is also notable that the weight has to be calculated again for the respective matched images whenever the template is changed, which makes the process of template matching to consume a lot of time. Despite this limitation, however, there is considerably higher accuracy when compared to scenarios where the starting point search technique is employed [18-20]. Given this superiority, the template matching technique was employed in the current investigation.
To construct the central moment, the target area’s centroid was selected and labeled as the center. The implication is that the calculation of the moment was the target area’s point relative to the target area’s centroid. Important to note is that the attribute did not exhibit any correlation with the target area’s position. Rather, it exhibited translation invariance.

When it comes to the case of the convolutional neural network (CNN), it can be seen that a major difference that emerges between the traditional multilayer perception network and the CNN itself comes in terms of the pooling and convolutional layers [20]. For the latter layers, they allow for CNN’s recognition of image details, yet other neural networks are known to be capable of only extracting data used in computation. For the CNN algorithm, its superiority is linked to three layers, which informed the model’s adaptation in the current investigation.

One of the layers is the convolutional layer. Here, its purpose was to scan the picture. The scanning process would target the range from top to bottom via a filter that had a fixed size. The purpose of this procedure achieved via CNN’s convolutional layer was to ensure that various local features were obtained. Indeed, these features formed the next layer’s input. Following ReLU function processing, values that were less than 0 would be exported as 0. However, in situations where, following ReLU processing, values exceeded 0, they would be exported directly. The outcome reflected the perceived feature map. Also, in the feature map, the respective points could be deemed as the region’s features in the original pattern, leading to their transmission to the layer that followed. For the CNN algorithm, therefore, the convolutional layer was used for the purpose of obtaining the pattern’s local features. Given the entire convolution operation outputs, then, there would be their transformation by using a nonlinear activation function.

Important to note, however, is that for a previous layer and the same convolution layer, the convolution operation would share a common weight. From previous studies, it is notable that the use of traditional deep learning networks towards image processing and recognition would call for the splitting of the original two-dimensional picture to establish a one-dimensional image [9-11]. Here, individual pixels would be treated as eigenvalues and transferred to the DNN architecture to be analyzed [13]. The eventuality is that for the input pixels, there is the loss of original spatial arrangement data [16]. In this study, therefore, CNN’S convolutional layer was useful because it allowed for the process of ensuring that the image’s spatial arrangement was maintained and that the input feature was a partial image that was obtained.

Another CNN algorithm’s layer that proved informative and informed the choice of the CNN model in this investigation entailed the pooling layer. Indeed, the pooling layer functions to ensure that there is the reduction of the size of the input picture. From some studies, this layer also allows for the reduction of the dimensionality of the respective feature maps [1], as well as the maintenance of crucial features [4]. Several merits are associated with the function of this layer of the CNN algorithm. For example, there is the reduction of over-fitting, the acceleration of system running, and the reduction of subsequent layers’ associated parameters [18-22]. In the same fashion as the convolutional layer, also, the pooling layer relied on a filter for the purpose of having various operation regions’ value extraction. Important to note is that the resultant output proved to be free from activate function.

The third CNN algorithm’s layer was the full connected layer. Here, the layer reflected the general neural network. Thus, feature extraction was achieved by the convolutional layer and image parameter reduction achieved by the pooling layer, with the full connected layer receiving the feature information to engage in the classification process.
Indeed, there was the connection of the respective neurons to the given previous filter’s pixel. For the respective connected weights, they were identical, allowing for their sharing in the same layer. However, it is also worth indicating that the respective connections exhibit unique and unrelated weights, implying that some considerable computing resources were likely to be consumed by the full connected layer. Whether this limitation was too minor to compromise the overall system efficiency and performance enhancement was a point of interest, which was clarified in the results and discussion section.

3. EXPERIMENTAL RESULTS AND DISCUSSION

With an image obtained by the CCD camera, with a given position in the image having the light spot established, there was the preliminary searching of the light spot image center’s range. This process is demonstrated in the figure below.

![Fig.2. Preliminary searching of the light spot image center’s range](image)

After the program established the light spot’s region, there was the displacement of the center point. This displacement led to the overlapping of the center of the CCD image, as well as an increase in the magnification of the CCD. Indeed, the increased magnification ensured that the CCD coincided with the light spot zone’s size. In turn, there was the separation of the light spot zone, completing the first search.

As mentioned in the methodological section, searching for the laser spot zone was achieved via the system’s utilization of a CNN. Given images that had various incomplete light spot modes and complete light spots, there was the training of the neural network. This training process sought to ensure that the program could judge or determine the image’s light spot position rapidly and with considerable accuracy. Upon the successful positioning the light spot zone in a given image, given an initial part, the light spot zone’s center was used as the center of the image. Here, there was deviation from the real center of the light spot, with the system treating the positioned laser spot zone as that which was not necessarily a complete light spot. At this stage, there was the measurement or determination of the distance between the light spot center and the center of the CCD image, allowing for the shifting and overlapping of the two centers.
In Figure 3 above, the regional center image did not reflect the center of the light spot, and it is presented alongside the incomplete laser spot image. The processing modes were two in this case. Also, regardless of whether the resulting light spot was incomplete or complete, it would be judged relative to the light spot zone’s ratio. For the case of the complete light spot, there was the extraction of its centroid point, which was achieved via the centroid technique. In turn, there was the calculation of the distance between the light spot center and the center of the CCD image. The process would culminate into the movement of the center of the image to have it overlap the center of the light spot. In situations where the light spot was not complete, there was the calculation of the invariant moments relation to the image’s incomplete light spot zone, eventually having it matched with the case of the preset light spot source image. The matching process sought to ensure that in the light spot, the centroid of the partial light spot zone had its position established. In turn, there was the calculation of the distance between the light spot center and the center of the CCD image, moving the image center to ensure that it overlapped the center of the light spot.

Given various sample numbers, the applied system’s positioning effects were then described. To have the neural network trained, positive samples that were used were 100, 50, and 25. The following figure demonstrates the experimental results that were achieved via the use of 50 negative samples and 25 positive samples to have the neural network trained. From the figure, the implementation of the proposed program saw the complete light spot positioned successfully, but still, some misrecognition was experienced. Also, in the figure, it can be seen that there was no successful recognition of the incomplete light spot. To have the results improved while implementing the proposed system, it (the program) was trained again, and the sample number increased.

The figure 4 above shows the results that were obtained after using 25 samples. As the study progressed, the focus shifted to the case of 100 negative samples and 50 positive samples, seeking to discern the behavior of the system, with those samples used for the purpose of neural network training. At this point, as it is highlighted in Figure 5 below, there was improvement in complete light spot misrecognition. However, it is important to note that still, the light spot region (only) could not be positioned. From the figure, it can also be seen that numerous misrecognitions were evident, but
incomplete light spots had their position recognized accordingly. To have the accuracy of the system improved, for a second time, there was the training of the network, with the sample number also increased.

Fig. 5. The map positioning of complete and incomplete light spots.

The figure 5 above shows the results that were obtained after considering 50 positive samples. There was further training of the neural network, with 200 negative samples and 100 positive samples used. At this point, findings indicated the program’s capability to have complete light spots’ region positioned successfully. At this point, the study noted a marked reduction in the probability of the program’s misrecognition. However, for incomplete light spots, they could still not be positioned.

For the three sample numbers that were used and the size of the feature region changed while having the neural networks trained, the table that follows shows the findings that were obtained. The motivation was to have 100 target images recognized. From the results, it can be seen that there was a significant increase in the accuracy relative to the sample number. For the case of the result candidates, they had misrecognitions and the corrected results. On the other hand, the target images’ results minus the result candidates depicted the program’s inability to have the number of targets recognized.

| TABLE 1 . THE LIGHT SPOT POSITIONING SYSTEM’S EXPERIMENTAL RESULTS |
|---------------------------------------------------------------|
| Number of Positive Samples | 25  | 50  | 100 | 100 (reduce feature region) |
| Number of Negative Samples | 50  | 100 | 200 | 200 |
| Number of Target Images | 100 | 100 | 100 | 100 |
| Result Candidates | 74  | 90  | 96  | 96 |
| Correct Results | 40  | 69  | 88  | 96 |
| Accuracy (%) | 54.05 | 76.66 | 91.66 | 97.96 |
| Classification Accuracy (μ) | 0.37 | 0.284 | 0.245 | 0.14 |

From the table 1 above, it can be seen that still, there were some misrecognitions in the system. The outcomes could be attributed to the position that it was the same neural network that was used for the purpose of recognizing the incomplete light spots and complete light spots. Also, the results could be attributed to a situation in which it was only the partial zones that were positioned, even at a time when there were complete light spots. Similar, at the platform, when the laser was shot, there was a decrease in brightness outward in relation to the center spot of the laser, with particles in the air scattering the laser partially. It can also be inferred that due to the partial black regions’ brightness, visual recognition was likely to be difficult. With the bright zones’ mode being closer to the light spot’s sample, misrecognition was more likely to arise.
Given the outcomes that were obtained after implementing 100 positive samples, there was a successful determination of the complete light spot’s region. From the case of the system flow, it was to the positioning regional center that the CCD image center was moved, eventually established as the template image. In turn, there was the calculation of the region’s aspect ratio, as well as that of the template. The procedure saw the program’s resulting template’s aspect ratio stand at 1.027. With the identification of the complete light spot, there was the calculation of the template image’s invariant moments, with the first moment then considered. Here, the light spot region’s barycentric coordinates formed the first moment and are shown in the figure below.

![Fig. 6. Light spot centroid positioning.](image)

In the culminating stage, there was the calculation of the distance between the center of the light spot and the center of the image, followed by the removal of the CCD camera. Here, there was the overlapping of the light spot center and the image center, allowing further for the second-time alignment of the light spot center. The figure below illustrates these procedures and experimental outcomes.

![Fig. 7. An illustration of the second alignment.](image)

For the laser spot, there was also the development of a gray level histogram. From Figure 8 below, it can be seen that the image center and the light spot center had their positions developed. Also, there was the establishment of the distance between both centers, achieved via coordinate relationship calculation.
When it came to the mean errors concerning the established light spot center and the image center, they were calculated after the system conducted the process of positioning the light spot for various sample numbers. Here, 1 pixel was equal to 0.11 micrometers. From the results, this study established that with an increase in the number of positive samples, there was enhancement in the features. Also, there was shorter time of the shift to the center of the light spot, with the first positioning shift having its center get close to the light spot’s center. The table below illustrates these findings.

**TABLE 2. SELECTED SAMPLE NUMBERS’ RESULTANT LIGHT SPOT POSITIONING’ MEAN ERRORS.**

| Number of Positive Samples | 25  | 50  | 100 | 100 (reduce region) |
|----------------------------|-----|-----|-----|---------------------|
| Average Mis-distance (pixel) | 3.567 | 2.579 | 2.224 | 1.273 |
| Average Mis-distance (μm)   | 0.37 | 0.284 | 0.245 | 0.14 |
| Detection Time (s)          | 0.5 ~1.6 | 0.5 ~1.6 | 0.5 ~1.6 | 0.5 ~1.6 |

After establishing the recognition region’s invariant moments, there was the performance of the similarity matching process relative to the complete light spot’s entire points’ invariant moment matrix. Here, the complete light spot’s entire points had been obtained in advance. The process culminated into the exporting of the maximum matching weight’s coordinate value. The following figure highlights these results.
Fig. 9. The weighting matrix of the invariant moment similarity.

From the findings demonstrated in Figure 9 above, given the complete light spot, the incomplete light spot had its position established. With the distance between the centroid of the complete light spot and the image center established, the CCD’s position could be moved, with the search for the center spot also completed.

Fig. 10. An illustration of the light spot centroid and the image center of the incomplete light spot’s relative positions.

In an industry such as the healthcare sector, it is worth noting that the devices used to acquire images have undergone tremendous advancement. Due to this progress, the resultant data has become so large that the attribute of big data has evolved. Indeed, these paradigm shifts make it interesting and challenging when it comes to the practices of image processing and analysis. With the marked growth in medical modalities and images, there has been a demand for medical experts to embrace extensive efforts, yet they have remained prone to human errors, with large variations also likely to be reported across various experts. As such, techniques of machine learning have been embraced, aimed at having diagnosis processes automated. Despite these efforts, it remains notable that the case of traditional machine learning techniques holds that they do not exhibit adequate levels of sufficiency, especially in situations involving complex problems. With machine learning and high performance computing combined, therefore, big medical image data can be handled adequately, yielding more effective and accurate diagnoses. This study’s results have demonstrated that apart from aiding in feature selection and extraction, deep learning exhibits the ability to construct new features. Also, deep learning is seen to promise to stretch beyond aiding in disease diagnosis and steer improvements in the
measurement of predictive targets, having offered actionable predictive algorithms that efficiently support the work of physicians.

Another trend that this study has established is that for diseases to be diagnosed more accurately, aspects of image acquisition and interpretation play an informative role. In the last few years, there have been substantial improvements in the nature of devices of image acquisition, especially in relation to radiological images that exhibit higher resolution. Some of them include MRI, CT, and X-Ray scans. In the wake of these images, this study has given insight into the role of image processing technology in yielding automated image interpretation. Through deep learning, neural network algorithms are seen to gain application. For example, this study’s proposed system is deemed insightful and applicable to healthcare practical situations because its superiority in performance is confirmed when compared to traditional techniques, allowing for the identification of indicators such as those of tumors for the case of MRI scans, as well as cancer in blood. With more hidden layers, deep learning has been found in this study to improve on artificial neural network (ANN), whereby it offers higher levels of abstraction, as well as marked improvements in the process of image analysis. here, some of the additional practical scenarios to which this study’s findings lend themselves include medical imaging, face recognition, speech recognition, and object detection.

The current study has established further that deep neural networks, relative to image processing, play a crucial role because of their capacity to have various layers of neurons stacked hierarchically. The proposed system, in particular, is seen to conform to and reflect this merit because of its capacity to form hierarchical feature representations. Also, the proposed system’s gigantic modeling capacity implies that through deep neural networks, all potential image mappings could be memorized, coming after successful trainings with adequately large knowledge database. At this point, it can be inferred, therefore, that this study’s results are contributory to the current state-of-the-art, whereby it allows for the making of intelligent decisions such as the extrapolation and interpolation of cases that could be otherwise unseen. Also, the proposed system is seen to point out the critical manner in which a major impact is generated in relation to medical imaging, as well as computer vision. With the system also projected to gain application to situations such as those involving voice and text processing, the convolutional neural network that is used simply points out how deep learning algorithms play a critical role relative to image processing at the industry level.

In this study, another trend that is worth acknowledging is that the performance of CNN was compared to that which had been reported previously in other experimental studies. For the CNN algorithm, it can be observed that the resultant drawback with which it tends to be associated is that it demands a lot of labeled data before achieving the image classification role – for the case of image processing. However, its positive side, as established in this study, is that it comes with very good performance and that the model learning process is fast. Another notable point concerning the CNN algorithm was found to hold that it exhibits superior performance when applied in contexts involving two-dimensional data, especially because it comes with convolutional filters that could allow for two-dimensional transformation into three-dimensional systems or architectures. For the case of the deep neural network (DNN) with which CNN was compared, its positive side is documented to come in the form of its wide usage due to great accuracy [2]. However, the DNN model also exhibits drawbacks, whereby the process of system training is not trivial [11]. This drawback is attributed to the observation that there is the propagation of the error back to a previous layer, with the model’s learning process also deemed much slow.

Previous studies have also focused on and documented the nature and performance of the recurrent neural network (RNN). For this algorithm, it is worth indicating that it exhibits the capacity to learn certain image sequences, sharing loads across all neurons and steps [3]. For this case of the RNN model, with many variations in existence, it is notable that there arise possible state-of-the-art accuracies when it comes to the aspect of image recognition and processing. However, when compared to the case of the CNN algorithm that was utilized in the current study, the RNN model exhibits many issues because of the need for big datasets, with additional limitation reported in terms of RNN-associated state of gradient vanishing. A question that arises here is the manner in which, in the future, the CNN algorithm, which was used in this study, could be tailored in a manner that incorporates positive performance aspects with which the other comparative models come while countering its associated demerit documented earlier.

4. CONCLUSION

When the concept of center spot search is considered, this study established that the matching process via the utilization of invariant moments tends to be faster when compared to situations involving the use of ordinary template matching. Here, the study demonstrated that when invariant moments are used, they allow for image digitization. At some
moment, the information that needed to be processed was about 72% less than the case involving the use of images for the operation of template matching. Also, for the source image’s every point, there was advance calculation of the invariant moment, which was then saved in a database, with the matched region’s invariant moments also having been calculated. In turn, there was the calculation of the similarity to the database on the focus. From the findings, it was discerned that in situations involving template matching, a weighting matrix has to be generated as the matching process progresses. Also, the process calls for the creation of the weighting matrix each time there is a change of the template, eventually consuming considerable or vast amounts of time. In relation to the proposed system, this study established that it relies on the ratio aspect when it comes to the checking of whether or not the target light spot is complete. With the nature of the light spot’s complete image aiding in or determining the selection of the positioning method, the proposed system demonstrated that for all images, the perceived complex computation is not required. Overall, the proposed system translated into significant reductions in the overall system’s load.

In the future, there is a need for further research or scholarly studies to focus on the behavior of the proposed system in environments that stretch beyond the image processing aspect and entail voice and text processing or recognition. Indeed, whether the proposed system’s perceived superiority in the image processing context might be felt and prove consistent when it comes to voice and text recognition and processing should be the focus of future studies, upon which inferences and conclusions might be made regarding the extent to which the model might contribute to the current and future state-of-the-art in feature recognition and processing.

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