

Toward Real-Time Quality Analysis Measurement of Metal Laser Cutting

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Abstract – Real-time quality monitoring in laser cutting applications is a key issue in high-tech steel manufacturing industries. The paper takes a relevant step in this direction by suggesting an automated system for intelligent quality analyses. The proposed system acquires frames related to the temporal evolution of sparks generated by the interaction of the laser with the metal as well as process-related parameters and, on the basis of extracted features, judges the quality of the current cut. It has been demonstrated the existence of a relationship between the shape assumed by the sparks and the quality of the final cut. Based on such relationship a quality analysis system has been designed, which integrates traditional image processing methods and soft-computing paradigms in order to control the balance between the accuracy of the quality analysis and the computational complexity (related to real-time constraints).

Keywords – Laser Cutting, Neural Networks, Quality Analysis, Feature Extraction, Image processing, Radon Transform.

I. INTRODUCTION

Laser cutting is becoming a key issue in the sheet metal and material processing industries [1, 2]. The principal motivation which pushed the rapid diffusion of such technology, in industry, resides in the process flexibility. In fact, current laser machines cut sheets of metal from few tenth of millimeter up to 25 millimeters with an appreciable speed and without any physical contact between optics and artifact. The superior cut quality arising from an optimized process poses another advantage: the edges of the laser cut are sharp, and it is not needed any subsequent post-processing.

Conversely, laser cut can be still considered as young -and difficult to handle- technology, which requires important progress to ease the process optimization phase. For instance, set-up of the numerous laser machine parameters is typically done by experts, with a time consuming trial-and-error procedure. During the cutting operation there can be shifts from the correct working point of the machine due to the instability of the laser source while erupted material can hit the optics with a severe impact on performance. In addition, the final quality of a cut is strongly dependent on the surface conditions of the envisaged workpiece (oxidation, roughness); even very small variations in the metal reflectivity may cause high variations in the absorbed energy. This negatively affects the reproducibility of the laser-based metal welding process.

For such reasons an automatic detection of defects at early stages in metal manufacturing industries and the

measurement of the process quality are becoming one of the key issues regarding the important economic impact over the industrial process. Currently, operators perform the quality measurement of the laser cut pieces via offline inspection. The creation of an accurate cut quality measurement system working in real-time can offer a solution to that industrial critical point of the laser processing chain. A deeper insight of the literature of laser cut can be found in [1- 4].

In [2] it has been preliminarily verified the existence of a relationship between the shape of the sparks jet ejected during the cut phase and the final quality of cuts. The proposed system, having in input a digital sequence of images of the erupted sparks during the laser action and others process parameters (such as the cut speed and the thickness of the metal), demonstrated that the quality classification of the cut can be computed automatically. Unfortunately, the obtained throughput was not yet suitable for real-time usage and performance was not good enough.

This paper describes new relevant advances towards the development of a real time cut quality measurement system. A new composite technique -a proper composition of image processing methods and neural networks- is presented. The performance of the final system was validated using a large data set provided during an acquisition campaign carried out at Trumpf GmbH (Germany) for the EU SLAPS project. During the campaign a camera was placed to capture the shape of the jet generated during the cut process as it is shown in fig. 1.

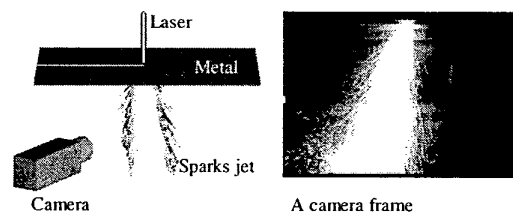


Fig. 1. Camera position and an acquired frame

In a perfect cut the metal edges should be perfectly squared and continuous, without any residual melted material on them. Typical defects detectable in laser cut pieces are shown in fig. 2. The edges can be not perfectly squared (fig.

2.c), discontinuous (fig. 2.b), with rough cut surfaces (fig. 2.a), or with small pearls (ejected melted material solidified around the edges called *pearls of burrs* fig. 2.d-e-f). These kinds of cuts are considered not acceptable.

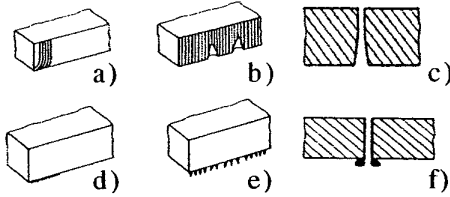


Fig. 2. Defects and sections: a) and c): drag; b): holes; d), e), and f): pearls (Courtesy of TRUMPF GmbH)

The automatic quality classification system can be developed by defining four indexes characterizing the sparks shape [2]. The first index is a Boolean value, indicating the presence of the sparks jet in the image (JP). The last three indexes describe:

- the inclination of the spark jet (α). The angle is strongly related to the cutting speed and the thickness of the metal.
- The wideness of the “nucleus” of the spark jet (β). It is related to the “excessive drag” phenomenon. In this case the final edges are not perfectly squared.
- The whole opening angle of the jet (γ). Strong difference between the γ and β angles can reveal abnormal situation in the sparks jet, for example divided jets (typical in discontinuous cuts).

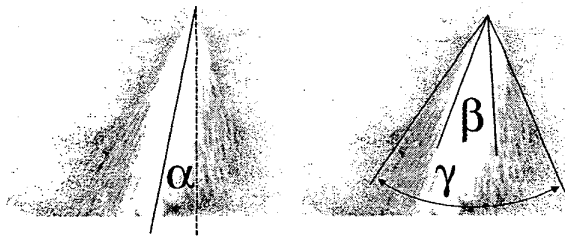


Fig. 3. Indexes definition for a single frame. On the left α (inclination of the nucleus w.r.t normal). On the right β (wideness of the nucleus) and γ (wideness of the sparks jet).

Since there are no exact definitions of what is the “nucleus” or the “whole opening angle of the jet”, the optimum definition of indexes was assumed as the one that optimizes the behavior of the final quality classifier.

The final classifier can exploit additional information coming from the field: the state of the cut system (i.e. cut speed, type and thickness of metal, laser type etc.). Cuts are classified in three classes: acceptable, not acceptable and not classifiable (ambiguous). The latter class is related to cut metal pieces that have an intermediate quality. Such dubious situations can be evaluated by traditional direct edge inspection. A good classifier must minimize classification errors and dubious cuts.

II. THE ARCHITECTURE OF THE SYSTEM

The classification system can be decomposed in three main blocks, as depicted in fig. 4. The first block receives a video from the camera and a set of parameters characterizing the status of the cutting process. The video is sampled, hence generating a sequence of single frames and synchronized with data provided by the sensors. The rate of the produced frames is 25 per second.

When the cutting process is in progress (i.e. the laser is active) each frame is processed and classified (block 2 in fig. 4). The classification of the whole cutting process is performed by the final cut classifier (block 3 in fig. 4) using the array of the single frame classifications.

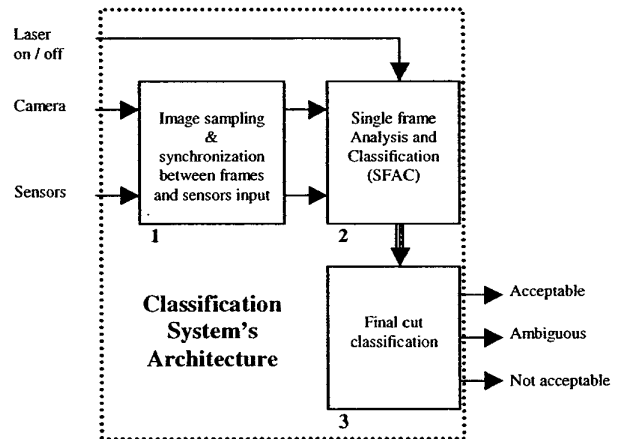


Fig. 4. Overall architecture of the classification system.

Many classification rules can be adopted for the final cut classifier, for example the “worst case” rule specifies that if a frame is classified as *non acceptable*, the entire cut is rejected. These kinds of rules, however, enhance the probability of discarding an acceptable cut, and should be used for processes with very high quality needs. More sophisticated rules may consider different thresholds for *ambiguous* and *not acceptable* frames to classify the total cut. Cuts classified as *not acceptable* can be directly discarded but *ambiguous* cuts can be further examined off-line.

The core of the final system is the *single frame analyzer and classifier* (SFAC, block 2 in fig. 4). This module processes the image of the sparks ejected during the cutting process. The task is critical in the processing chain since the shape of the sparks jet is extremely variable and the computational complexity of the module is constrained from the real time requirement (in the case of a PAL video stream, which has a frame rate of 25 Hz, each frame must be processed in less than 0.04 s). The SFAC addresses such issues with a composite method [5]. In particular, the module combines the neural network’s aptitude to facing the variability in the input data and the effectiveness of traditional image processing techniques.

The structure of the module is given in fig. 5. The module can be decomposed in three main blocks. When the laser is active, each single frame acquired by the camera is processed by a *jet presence detector* (block 2.1) and a *jet features extractor* (block 2.2). The outputs of the latter sub-modules are the features presented in the previous paragraph: JP, α , β , γ . The extracted features and the signals coming from environmental sensors (detecting the cut speed, the type and pressure of the used gas and the focus distance of the laser) are inputs to the *single frame classifier* (block 2.3) which classifies the examined sparks jet as belonging to an acceptable, ambiguous or not acceptable cut.

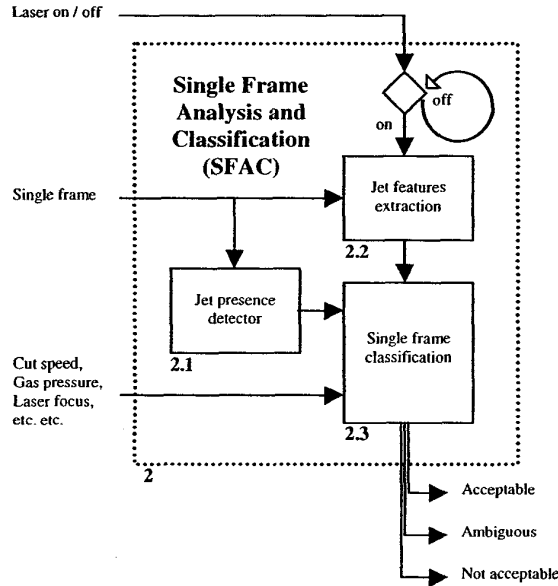


Fig. 5. Detail of the single frame analyzer and classifier block (SFAC).

II.1 The Jet Presence Detector

The *jet presence detector*, having in input the image retrieved from the camera, processes the *jet presence index* (JP). The index is a real value ranging from -1 (absence of jet) to 1 (presence of jet) and it is implemented with a neural network. This choice is motivated by the consideration that it is not possible to provide an exact definition of the “jet presence” concept: only examples are available to define the desired behavior of the module. Furthermore, the sparks jet can vary widely in shape, intensity and position in the image (fig. 9). Actually, the laser can be moved with respect to the metallic slab during the cutting process but the camera-shooting angle is fixed. On the contrary, the cut is performed by moving the metallic slab and maintaining the laser fixed only occasionally.

To obtain a detection algorithm which is effective, not computational complex and independent with respect the

position of the jet vertex, a neural network was trained. The training image set was composed by $N \times N$ squared down-sampled images with:

- no jet (but with different backgrounds and spurious sparks),
- sparks jet present only in their central position.

Afterwards, the following procedure was used to create the output of the *jet presence detector*:

1. Down-sampling of the input image (final dimension: N rows, M columns).
2. Creation of a sub-set of K images by cropping the original image using an $N \times N$ horizontally window, shifted by a step equal to M/K (the dotted area in the fig. 6, left). To avoid that an image belonging to the K sub-set (the ones taken from the more external steps of the cropping operation) can contain blank columns, a “zero padding” operation is required (fig. 6, right).
3. Each image of the K sub-set is processed by the neural network, providing a K-sized vector of presence indexes.
4. The final *index of presence* of the original image is the highest value present in the K-sized vector.

The computation of the obtained neural network, over all the K images of the sub-set, is lower than the ones of a neural network trained to identify the jet presence in a generic position. The designing of training set is also less problematical. Using $K=9$ a very effective behavior was obtained, discriminating the presence of jets with a computation amount of 3000 FLOPS for each image in the K sub-set, obtaining therefore a detection algorithm which overall requires only 27000 FLOPS.

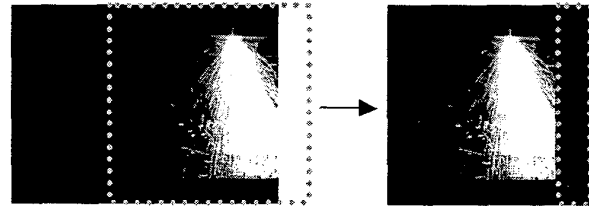


Fig. 6 On the left: cropping a squared peripheral sub-image from the original image (which contains a jet in its right side). On the right: the obtained sub-image, and the “zero padding” operation required to restore its background. The sparks jet is now centered.

II.2 Features extraction

The purpose of the *jet features extractor* module is to retrieve the vertex position of the sparks jet and, by using this information, measure the α , β and γ angles. This module is implemented by traditional image processing techniques.

The processing starts by separating the sparks jet from the background, and from all the surrounding small and isolated sparks. The separation is made through two phases. In the first phase the image is segmented using a luminous intensity high-pass threshold binarization [6, 7, 8]. Since the luminous intensity of the sparks jet can noticeably diverge between

different images, the threshold value is found with an adaptive method. This method approximates the image luminous intensity histogram with a bimodal function as described in [8] and identifies its middle local minima. In this way the function is divided in two parts, which describe respectively the luminous distributions of the sparks jet and the image background. The second phase involves the removal of small and isolated parts of sparks. To this end we applied a morphological opening filter [8] to remove the spurious effects, while the rest sparks are cleared depending on their size and comparing it with that of the main sparks jet. An example of this separating process is given in fig. 7.

Once the sparks jet is separated from the rest of the image we have to identify its main axis. The processing is achieved by using the Radon Transform (RT) [9]. This transform maps the image into a bidimensional function, defined in a space in which every point of the map (the co-domain) match to a line in the image plane (the domain). A typical feature present in all studied sparks jet is that their main axis can be easily retrieved by looking at the coordinates of the maximum value of the RT (fig. 8). Once the main axis is available, its intersection with the horizontal line defined by the jet upper limit provides the *sparks jet vertex*.

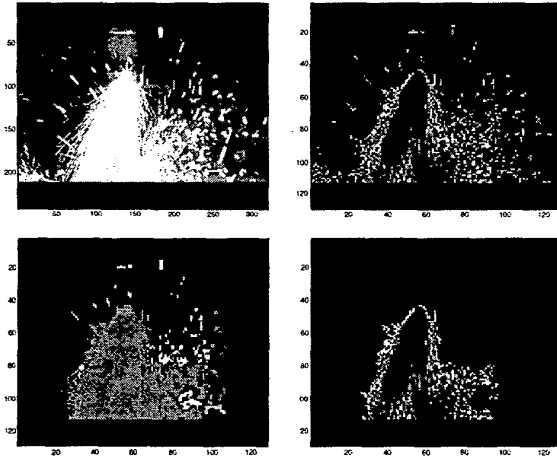


Fig. 7. An example of sparks jet separation from the background and from all the surrounding small and isolated sparks.

The α , β , and γ angles are estimated with linear regression techniques. In more detail, the β angle can be found by identifying the lines that best separately fit the points that mark the left and the right edges of the sparks jet, and forcing the lines to cross the jet vertex. The α angle, instead, is determined by the line that, while intersecting the vertex, best fit the midpoints of the jet nucleus. To obtain these lines and the required set of points, first of all an adaptive threshold high-pass filtering is applied to the original image. By separately processing each row of the image, the α and β sets of points are located by selecting the middle and the

peripheral points of the sparks jet. These three sets of points can be located by integrating the light intensity over the current row and selecting the point where the integral value is equal to 10%, 50% and 90% of the maximum. The γ sets can be retrieved in the same way, using a smaller threshold value for the image luminous intensity high-pass binarization.

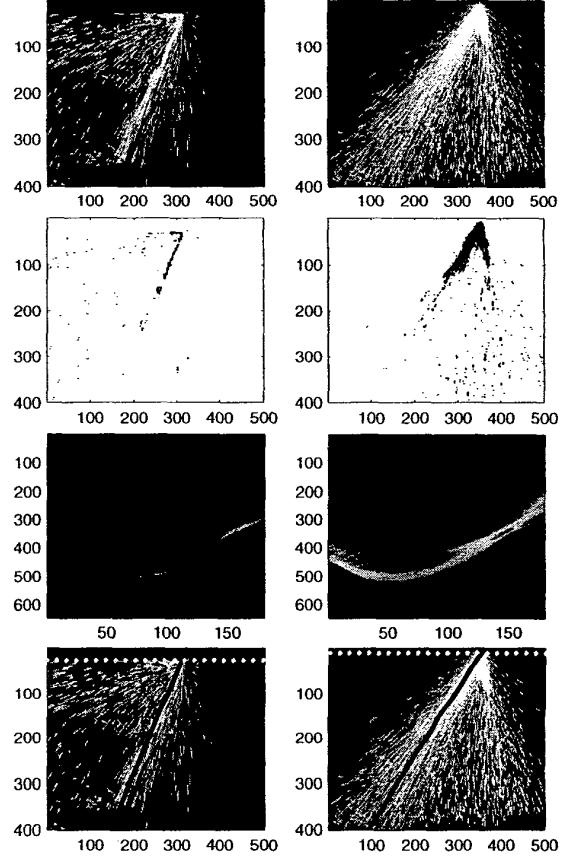


Fig. 8. An example of Radon Transform of sparks jets. The vertex of the jets is retrieved by locating the intersection of the horizontal line (defined by the jet upper luminous point) and its main axis

The jet features extractor works by using re-sampled images to lower resolution (128x128 pixel). An analysis of more than 17500 frames showed that the maximum amount of FLOPs used is approximately 11 flops/pixel, with a minimum around 4.5 flops/pixel and a mean value of 6.5 flops/pixel. These values are promising since it is expected that they can support a real-time operation for the system.

Fig. 9 shows some examples of the processed frames, where the γ lines evidences the left and right edges of the sparks jet. Conversely, the β lines are located more closely to the jet core and, often, overlap the γ ones. In the middle of the core the α line is traced, alongside the main spark jet axis (provided by the RT), which is drawn with a lighter gray.

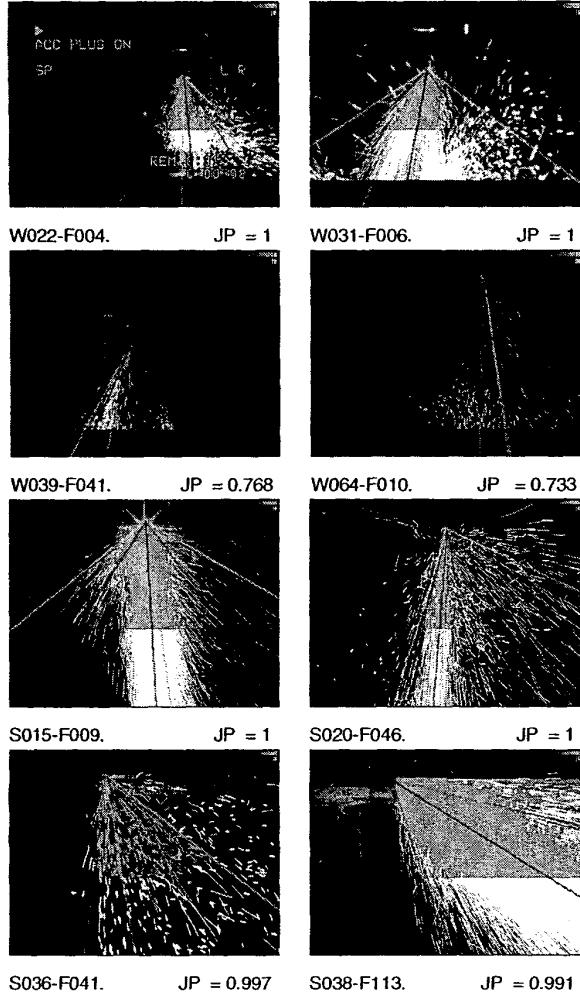


Fig. 9. Some examples of the frame analysis results.

We noted that the lowest 2/5 part of the frames are excluded from the processing since they are not relevant and allow for a reduced computational burden. In this way, way the largest part of sparks eventually rebounded by the floor, (which may false the RT results), can be suppressed. Finally, for each frame the output of the jet presence detector (JP) is provided.

Fig. 10 shows a cutting process carried out with a variable speed (from 2 m/s to 4 m/s, in five equally spaced steps). A plot of the cutting speed and the α , β and γ angles associated to each frame is provided. The frames in which the quality of the cut is limit/acceptable correspond to the penultimate speed step. All the frames with not acceptable quality fall in the last speed step (the dark gray area). This example clearly shows the correlation between speed, angles and cutting process quality. It is possible to note that for each speed step

there is a corresponding variations in the angles. It is particularly evident in the last two steps, where α starting from about 0 degrees suddenly decrease to -20 and -60 degrees. Since the spark shown in the example has a very compact nucleus, it is possible to note that the β and γ angles are overlapped in almost all frames.

Typically β tends to differ from γ in correspondence with each speed change. In fact, the sudden variation of speed creates discontinuity in the jet boundaries. The α and β indexes are more stable in value with respect the cut speed. The shape of the jet actually widens when it becomes less tilted (maximum β corresponds to $\alpha = 0$). For strong inclinations of the jet (high cut speed) β decreases again. This different behavior can be explained by noting that for high cut speed -and using a constant laser power- less material per length unit will be erupted causing the thinning of the spark jet.

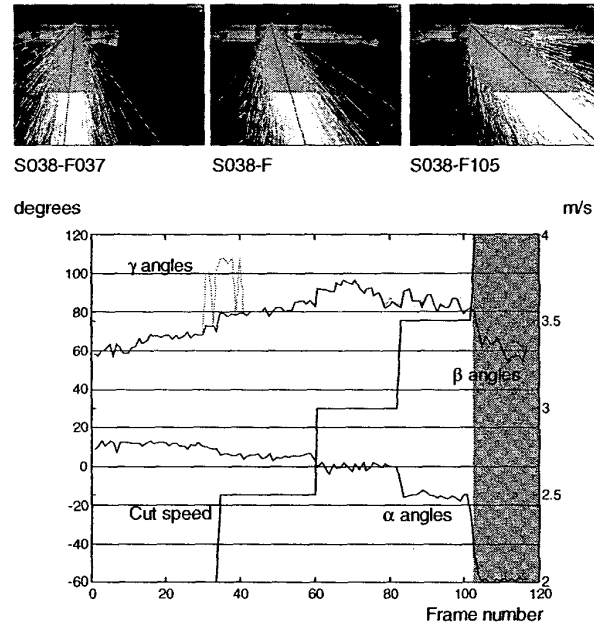


Fig. 10. A cutting process with variable speed. Up: three frames from the processed cut. Bottom: the α , β and γ angles w.r.t the cut frame number (time). The penultimate speed step produce frames with limit/acceptable cut quality. The red area indicates not acceptable cut quality (frame rate=25/sec).

III. CLASSIFICATION RESULTS

The classification of each frame is done by making use of a k NN (k Nearest Neighbour) classifier [10, 11]. Once the norm to calculate the distances of the vectors is fixed, the parameters to be set in a k NN classifier are:

- the number of neighbours to be used for the classification
- the number of sample that are stored in the classifier.

Both of them influence the accuracy and the computational complexity of the classifier. In the k NN the inputs are mapped in a M dimensional space, where M is the number of features used for the classification. When an unknown input is classified, the k nearest vectors in the stored set of the k NN are selected. It can be done by simply measuring the distance between the unknown input vector and all the stored ones. In our case the input vector is composed by the features extracted: α , β , γ , the cutting speed, the gas pressure and the laser focus.

A set of more than 12800 frames -classified by expert users- has been used to train and validate the KNN classifier. The used training set was partitioned including the 60% of the available frames by random extraction, and cross-validating the obtained classifier by using the remaining 40%. By using the previously described validation set of images the mean classification error for this k NN was about 0.18%, with a standard deviation of 0.09%, a minimum of 0.09% and a maximum of 0.29%. These results show that the features extracted from the cutting process provide excellent indications over the quality of the final manufactured pieces.

IV. CONCLUSIONS

In this paper was presented an automatic system for quality analysis measure. Image processing techniques and neural networks was combined to achieve good accuracy and real-time performance.

The features extraction system has been tested over more than 17500 frames and cross-validation showed an excellent accuracy: the mean classification error was about 0.18%.

Actually a fully software and interpreted version of the final algorithm (developed in Matlab) takes about one second for each frame to perform the complete automatic quality classification on a Pentium III PC at 550 Mhz.

Of course the maximum input frame frequency can be incremented by optimizing and compiling the code and/or implementing parts of the algorithm with dedicated hardware. The required frame rate for on-field real-time functioning is quantifiable as about 10 frames per second. For this reason the proposed system can be considered as effective solution to the presented problem.

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