International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-6, March 2020

A Robust Automated Vision Based Filamentous Steel Strip Crack Detection System Based on Neuron Model Segmentation

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Abstract*: *Crack detection has always been a dominant requirement for steel industries to ensure quality production and seamless infrastructure maintenance. However, application complexities and defect morphological differences make existing approaches confined. Steel-strip surface often undergoes scratch, crack and fatigue conditions during production. Manual crack detection schemes are no longer effective in current day complex environment. Amongst major steel strip crack detection approaches vision based techniques have found potential; Filamentous crack which is caused due to fatigue or strain is fine-grained and thin and hence highly difficult to be detected by classical morphology and static threshold based schemes. In the present work steel strip surface (filamentous) crack detection system has been developed which employs Varying-Morphological Segmentation (VMS) also called Neuron-Model Segmentation (NMS) in conjunction with local directive filtering and active contour propagation. The proposed method can be stated as an augmented variational framework that employs multi-directional filters for local crack-region identification followed by automated multi-directional region growing and iterative contour evolution which performs level set energy minimization to achieve accurate crack detection even under topological non-linearity and varying illumination conditions Simulation results with standard benchmark data has confirmed that the proposed method exhibits satisfactory performance for steel strip surface cracks.

Keywords: Automatic Steel Strip Crack Detection, Neuron-Model Segmentation, Active Contour Propagation, Region Growing, Level Set Concept.

I. INTRODUCTION

In the last few years high pace globalization, industrialization and the zeal to penetrate global market for accomplishing better market share have revitalized manufacturing industries to produce quality products. Amongst the major manufacturing segments, steel industry has always been the driving force behind other industrial enterprises and hence maintaining optimal quality of production with better resource utilization has always been the challenging task for the manufacturers. Lean production systems recommend optimal quality of production to avoid any wastage during supply chain. Amongst major steel products, the production of flat steel-strips dominates over other products. In such case, maintaining optimal quality of steel strip production while assuring both metallurgical perfection as well as physical (say, morphological) aesthetics is vital. During application steel strips might undergo varied wear and tear resulting in cracks that eventually lower reliability and life of the system. On the other hand, physical phenomenon within pre-installed infrastructures often undergoes issues like crack, scratch, disjoint etc that if not monitored properly could result in hazardous consequences. Therefore, identifying the presence of crack can not only avoid any probable fault but can also help manufacturers to avoid pushing faulty steel-strips (crack) into market (i.e., supply chain). Practically, crack is one of the most common faults in steel-strips and hence requires optimal inspection to avoid any catastrophe. Classical approaches use manual inspection which often imposes processing time and sometime inefficiency, thus demanding a better automatic crack detection scheme [1]. In industrial activities certain certified inspectors and/or structural material engineers perform condition assessment of the steel strip after production or in pre-established infrastructures. This process needs to be repeated after a certain interval to avoid any unexpected consequence. Contrarily, manual inspection over a large amount of steel strips is highly tedious and time consuming. To avoid such limitations automatic crack detection systems can be of utmost significance. Undeniably, the nature of crack or allied topology often decide efficacy of an approach to perform surface crack detection. Approaches functional for straight crack detection or high-width crack morphology can't be suitable for detecting cracks with fine grained structure or thin filamentous crack region. This necessitates the development of a more robust and automated steel strip crack detection system. This research mainly focuses on developing a novel automatic crack detection system. Though a few approaches have been proposed in the past such as Magnetic Field Flow (MFF) [2][3], Eddy Current based approaches [4], ultrasonic inspection etc; however, the ability of vision based technology has been found better than other solutions.

Manuscript received on February 10, 2020.
Revised Manuscript received on February 20, 2020.
Manuscript published on March 30, 2020.
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Computer vision based approaches can be vital to enable swift and more precise crack detection even under different illumination and topological conditions [1][5][6].

Being a low cost, flexible and easy to access technology, vision based scheme is the most sought after method for automatic steel-strip's crack detection [5]. In the last few years efforts have been made to exploit different methods like edge detection [7], percolation, textural analysis [8] - [10] [20] [26] [45], segmentation and local feature [11] -[13] based crack detection, region growing and classification [22][24][55] etc to perform crack detection [14][15]. Approaches depend on the efficacy of image processing a few efforts were dedicated to augment wavelet transform for crack detection [8] [16] [17] [27]; however, being static local threshold based scheme it lacked potential to perform filamentous or thin crack detection. Similarly, edge detection technique, was found limited especially under noisy steel-surface and topologically complex environment [7]. Approaches using morphological features [8] [26] [56] are confined due to presence of noise and non-linear topological conditions. Local percolation-based crack detection [18] was found better for surface crack detection over large crack region [19]; however, its efficacy could not be justified for very thin filamentous crack detection. On the other hand, the steel strips being produced these days are of different shapes and sizes that could suffer stress, strain and/or fatigue during its life cycle. Noticeably, such cracks often used to be thin and filamentous. A few other schemes like statistical filter [21] [25], morphological filter [22], Hessian matrix-based filter [28] and wavelets based approaches [29]- [31] have been proposed in the past to perform crack detection. The above stated approaches were predominantly surface-texture-morphology based models and can't be suitable for non-linear surfaces or sharp changing, topologically varying crack structures or coarse textural features on steel strip surface. A few approaches like Principal Component Analysis (PCA) and histogram based classification algorithm [32] were developed for crack detection; however, they were focused on large gap structural crack detection (i.e., bridge-crack, pavement crack or road crack detection). The applicability of these approaches may not be suitable for fine-grained and filamentous crack detection in steel strips. There are numerous conditions such as cluttered environment; shadow region etc where the classical approaches can yield false detection, especially for thin filamentous cracks. There are innumerable cases where cracks are caused by physical damage or factors such as residual stress in steel strips. Noticeably, these types of cracks often have complicated geometry and thin crack region that makes most of the classical approaches ineffective. In addition, non-linear growth in crack geometry and different branches or curves makes most of the existing approaches limited and therefore demand a certain more efficient and robust solution for thin and filamentous crack detection. Recently, an approach called region growing was proposed [33] [34-37] that in conjunction with the shortest path algorithm (with optimal graph-weight estimation) performed branched crack detection; though these methods were primarily focused for large width crack detection over road, pavement or bridge like infrastructures. Presently, there is no potential automated system developed so far to perform fine grained and filamentous crack detection on steel strip surface. In this paper a highly robust and efficient steel-strip crack detection system is proposed for filamentous and very thin cracks over steel strip surface. Unlike classical approaches, a novel Varying-Morphological Segmentation (VMS) concept that in conjunction with active contour propagation (CP) and level set concept enables highly accurate steel-strip crack detection even under different topological (branched neural of filamentous cracks) and varying illumination conditions. The proposed crack detection model comprises two consecutive phases in which firstly initial crack identification function was performed using multi-directive filters and Hessian matrix method. In the sub-sequent phase an automatic multi-directional region growing method is applied using active contour propagation with level set method. As an integrated solution, the proposed method can be stated as a variational framework supported by level-set where the level-set evolution tries to reduce specific energy functions to perform accurate filamentous crack detection and segmentation. Simulations with standard benchmark dataset as well as first hand collected data samples have exhibited that the proposed model performs satisfactorily even under different illumination conditions and different topological cross-point structures.

The other sections of the presented paper are divided as follows: Section II discusses the key existing schemes for steel crack detection, which is followed by problem formulation in Section III. Section IV discusses the proposed system. Results obtained are discussed in Section V and conclusion and allied future scopes are discussed in Section VI. References used in this research are presented at the end of manuscript.

II. RELATED WORK

This section briefs a snippet of the existing crack detection schemes and their respective strengths as well as limitations. Amongst the major steel strip surface crack detection schemes, eddy current based detection [4], thermography [38], Magnetic Flux Leakage (MFL) [2][3] and image processing based crack detection methods have been most explored. Kim et al [39] applied magnetic and ultrasonic approaches to perform steel slab crack detection. Wang et al [40] [41] assessed traditional thermography inspection method to perform crack detection; however, found it limited to perform steel surface cracks identification. As a novel contribution authors developed Thermal Pattern Contrast (TPC) mechanism for weak thermal signal detection using eddy current pulsed thermography (ECPT). With a similar motive, Slobodnik et al [4] also used the pulsed eddy current concept to perform crack detection in the electrically conductive steel plate. However, their effectiveness in current alloyed Iron materials with different structural features was suspicious. Understanding limitations of the classical MFL schemes, Okolo et al [2] proposed an optimized pulse MFL model that was further augmented by Tsukada et al [3] with unsaturated alternating current (AC) MFL for steel crack detection.

However, these approaches could not exhibit optimal solution, especially for the steel components with non-linear surface or inner surface crack topology [42].

To alleviate existing issues in MFL, Bouchalkha [42] used ultrasound waves to retrieve 3D images of pipeline inner surfaces. As an alternative paradigm, photoluminescence (PL) and infrared transmission (IR) images were used by Demant et al [43] to perform crack detection. The concept of pattern recognition was applied in conjunction with local (feature) descriptors and support-vector machine (SVM) classified defects in steel slabs [24]. However, this approach could not address the issue of non-linear and filamentous branched crack detection. Considering vision based approach, Hsu et al [44] focused on developing a fast vision-based surface inspection model that exploited crack features to perform defect identification. This method could not achieve optimal performance due to in-homogeneities in the microstructure. To address the issue, Huynh et al [48] developed automatic thin crack detection in pipelines using Dou-Edge Evaluation (DEE) scheme; but could not address the issue of filamentous crack identification and segmentation under different illumination and clutter conditions. Wang et al [46] explored the potential of the different image-based crack detection methods such as integrated algorithm, morphological approach, percolation-based method, and practical technique for steel sheet crack detection. Predominantly, this method was used for concrete crack detection which is often relatively thicker than the steel strip's cracks.

Applicability of vision based steel crack detection systems primarily depend on feature extraction, region of interest (ROI) segmentation and further classification for which retaining optimal feature identification is a must. Though the approach used watershed transform [47-53]; it lacked efficiency due to post-morphological segmentation and connected component analysis, which seems tedious for filamentous crack structure. In [48] Marik et al developed a fast linear single-sweep algorithm that generated all possible extreme weighted connected components in one dimensional real value signal. To further augment it, Elyounsi et al [49] enhanced ROI segmentation using an integrated mathematical morphology watershed and thresholding methods. This method in conjunction with the top-hat transformation performed crack detection for 3D Inverse Synthetic Aperture Radar (ISAR) Images. Wang et al [50] integrated watershed with top-hat transformation [49] for water body extraction in SAR image. Regardless, these approaches could not achieve object (specifically cracks) detection with non-linear topology and were found suffering from over segmentation issue. To alleviate this, authors applied post-segmentation approach called connected-component analysis (CCA) and chain code. Machairas [52] and Yuan et al [53] suggested watershed transform for super-pixel generation, through a spatially regularized gradient that could retrieve a tunable trade-off between super-pixel regularity and adherence to object boundaries. Though, Yuan [53] tried to augment watershed segmentation algorithm by means of a hybrid gradient and self-adaptive marker extraction, it could not address the non-linearity issue over the steel surface and varying crack topological conditions. Authors [54] introduced wavelet based Non-Linear Mean Square (NLMS) adaptive filter and thresholding to perform precise feature extraction, though it could not address non-linearity in surface quality and fine-grained filamentous cracks. In the recent years a few more efforts were made by applying cross-coupled neural network [55] to perform crack detection in images. Singhka et al [13] applied Artificial Neural Network (ANN) to perform defect classification over extracted features of steel strip surface. The authors didn't address the problem of thin and non-linear crack over steel strip surface. Wang et al [41] applied random forest algorithm to perform steel beam panoramic crack detection, though it can't be optimal for fine grained cracks on steel strip surface. Landstrom [56] applied morphology concepts and logistic regression based statistical classification to perform crack detection on steel slab surfaces. To achieve better accuracy for fine crack detection, Liu et al [57] suggested morphology concept with multi-scale enhancement and visual features; though it was designed especially for concrete crack detection. Considering the detection of cracks in images clicked from a larger distance Noh et al [58] performed ROI segmentation using filtering and morphological operations. While, this approach made effort to exploit local features for efficient classification the classical static thresholding based morphology confined its suitability for non-linear, thin and filamentous crack segmentation. No significant effort is seen in the literature towards enabling crack detection of fine grained and filamentous cracks over steel surface

III. PROBLEM FORMULATION

Unlike road-crack or pavement crack detection where the geometry or dimensional characteristics of the crack can be more perceptible, this research focuses on developing a robust approach to detect fine grained, thin and filamentous crack region segmentation over steel strip surface. This research method exploits the variational framework driven by level set, where level set evolution intends to minimize specific energy function to assist optimal and/or accurate filamentous crack detection. Considering topological complexity and cross-point structure, in the present work a novel Varying-Morphological Segmentation (VMS) model has been designed which can be visualized as the Neuron-Model Segmentation (NMS) to detect crack even under cluttered and shadowed environment. Inclusion of the proposed NMS scheme enables resemblance of the branched filamentous cracks to the neural structure which could be realized by region growing method based on which active contour evolution could perform crack region segmentation.

To perform filamentous crack region detection this paper proposes an integrated VMS framework which is executed in two consecutive phases. Firstly, Hessian matrix based local multi-directive filters have been initiated that help to identify local crack indicator function. On identifying local crack indicator function an integrated scheme comprising automatic multi-directional region growing and level set method has been developed that exhibits iterative active contour propagation or evolution to perform crack detection over steel strip surface.

To achieve total ROI segmentation, contour propagation (CP) is performed iteratively along the crack orientation (originating from seed or set-points). In the above stated paradigm identifying seed region or the crack origin is a complicated process which is either done manually by an expert or by automatic measure. A few existing approaches have made efforts to use multidirectional templates to estimate the direction for retrieving seed points along the neural medial axis. However, for automatic process local region growing concept can be a better alternative that could help detecting fine grained or thin (crack) branch. Other classical approaches like watershed transform which requires post-segmentation analysis such as connected-component analysis to perform overall segmentation, are time consuming. As a solution, the concept of branch-growing and connection method can be considered between the optimal set of seeds by estimating the shortest path; however, it suffers degraded segmentation accuracy in case of improper set of point selection. The other approach such as global method which employs pipeline-enhancement, segmentation, center-line detection and post processing requires image smoothing of the medial axis with spline fitting too might get affected by noise and clutter presence and hence can eventually affect the overall performance. Unlike classical contour evolution and region growing concepts, where user requires initializing or defining local seed-points for contour evolution, the present work proposes Otsu method based thresholding and an attractive force field function that enabled automatic contour evolution over image to perform crack segmentation. Summarily, the proposed model can be stated as an augmented variation framework driven by level sets that intend to minimize energy-functions during contour evolution to perform filamentous crack detection and segmentation over steel strip surface.

IV. SYSTEM MODEL

This section primarily discusses the proposed system and its implementation. The proposed steel-strip crack detection model is developed based on non-linear structure segmentation concept called the Neuron-Model Segmentation (NMS) or VMS. It exploits the concept of VMS that in conjunction with level set method and active contour propagation (i.e., region growing) enables precise filamentous crack segmentation. To achieve the eventual target our proposed model incorporates a number of sequential measures to derive automated filamentous crack segmentation scheme.

These are:

A. Defining Non-Linear (Tubularity) Flow Field (NFF) for initial region Identification,

B. Hessian Matrix based ROI Evidence Identification in NFF,

C. Modelling of an Enhanced NFF Model with Local Multidirectional Filtering,

D. Varying-Morphological Segmentation (VMS) model or Neuron-Model Segmentation (NMS),

E. Contour Propagation assisted Local Feature Extraction (LFE).

F. Local Attraction Force Field (LAF) design for automated filamentous crack segmentation.

The proposed method firstly derives a non-linear tubularity flow field (NFF) concept that enables easy implementation of thin-crack detection over steel strip surface under cluttered condition.

Once NFF model is derived, Hessian matrix based template matching using multiple directional filtering is done. Upon performing initial crack identification, it is followed by active contour propagation that in conjunction with level set method enables precise crack segmentation over steel strip surface.

The detailed discussion of the proposed segmentation model is given in the sub-sequent sections.

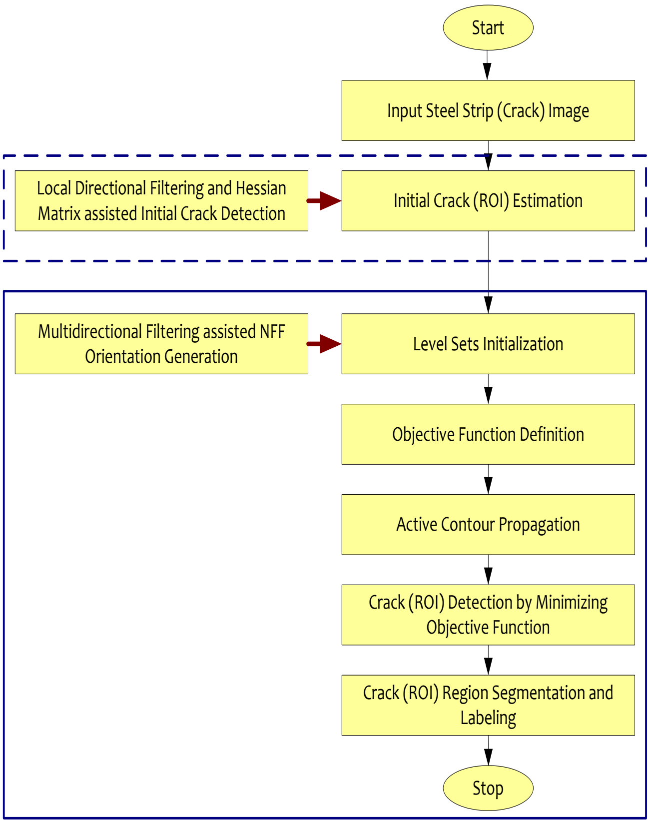

Fig 1. Implementation schematic of the proposed steel strip crack detection system

A. Defining Non-Linear tubularity Flow Field (NFF) for Initial Region Identification

In this phase the prime focus is on deriving NFF model so as to assist fine grained and very thin crack region identification, even under shadowed or varying illumination conditions. To derive it, the structure segmentation concept recommended in literature wad followed. [15]. The proposed NFF model exhibits segmentation by means of a Geometric Active contour (GAP) Propagation that exploits level set approach where it intends to reduce certain objective function. To achieve this, we have designed multidirectional contour propagation scheme as $C(x, y)$ that propagates in effect of vector field, called NFF. In this approach contour propagation is derived in terms of the equation (1).

$$\frac{\partial C}{\partial t} = \alpha_1 < V_1, \mathcal{N} >^2 \mathcal{N} + \alpha_2 < V_2, \mathcal{N} >^2 \mathcal{N} \qquad (1)$$

In (1), $\mathcal{N}$ signifies a unit perpendicular (i.e., normal) vector at each location of the contour $C(x,y)$. V_1 and V_2 present axial and normal component(direction orthogonal to it) of NFF depicting crack-orientation. Thus, the defined contour region $C(x,y)$ continues motion in such a manner that it propagates in the direction of crack-region (say, crack axis due to V_1 as well as crack-thickness due to V_2). In the present model, to control the speed of propagation two coefficients, $\propto_1$ and $\propto_2 > 0$. have been applied. In (1), $<.,.>$ states the operational rule signifying Euclidean inner product of operators. On conceptualizing the NFF model, it becomes important to identify crack region. Since, majority of the image based crack segmentation models employ template matching concept, in the present work Hessian matrix based initial crack region identification that employs two directional filters for achieving overall crack segmentation intrinsically.

B. Hessian Matrix based ROI Evidence Identification in NFF

Authors [15] found that the values of the propagation-speed control coefficients (i.e., $\propto_1$ and $\propto_2$) have direct impact on ROI evidence identification over curve evolution, and hence selecting a suitable coefficients can be obtained by (2).

$$\propto_1 = \propto_2 = R(x,y).R(x,y) \tag{2}$$

Noticeably, in above expression, x presents the image under study, while y signifies the position in the image. Equation (2) stated the NFF indicator function that hypothesizes a high scalar value $(\cong 1)$ at certain position, where a structure is supposed to be present, and a low value $(\cong 0)$ when there is no such structure available. In such cases, it is assured that the propagating active contour stops only when the magnitude of NFF indicator function reduces. Here, $R(x,y)$ was designed on the basis of Hessian matrix analysis, where the Hessian matrix for an image x at certain location y is obtained by (3).

$$H_\sigma(x,y) = [h]_{i,j}\ (1 \le i,j \le 2),\ f(x,y)\epsilon\Omega \tag{3}$$

In (3), x states the d-dimensional vector $(x_1, x_1, .., x_d)^T$, scale σ represents the square matrix. The Hessian matrix of d-dimensional image $f(x,y)$ (i.e., d-dimensional image x at location y) can be obtained as (4).

$$h_{i,j} = \frac{\partial^2 G(\sigma)}{\partial x_i\, \partial x_j} * f(x,y) \tag{4}$$

In (4), the variable $G(\sigma)$ signifies the zero mean normalized Gaussian kernel having the variance of σ^2.Typically, filamentous neuron used to be brighter than the background and hence becomes feasible to obtain scale space Hessian matrix that enables retrieving filamentous crack region of an image at a particular location of $f(x,y) \in \Omega$. Considering that the crack regions are depicted in terms of varied intensity distribution from the steel-strip surface region, it becomes easy to retrieve the scale space Hessian matrix that further helps in obtaining evidence of tubular crack at a certain position over the digital image (of steel strip surface image). Owing to the undeniable fact that the crack regions are typically designed or defined in terms of piecewise rigid templates when estimating Hessian matrix, classical crack detection approaches cannot deliver optimal

performance, specially for the complex crack geometries such as filamentous cracks. The classical approach may result in local structural discontinuation and hence may yield false detection output. To alleviate this issue, we introduced an enhancement by employing a specific local attraction force that lines the (natural) fragmented structures. Further to augment time efficiency in this paper a novel evidence filter concept has been applied to detect tubular filamentous cracks over steel strip surface. The detailed discussion of the proposed NFF multidirectional filtering based crack detection scheme is given in the sub-sequent section.

C. Modelling of an Enhanced NFF Model with Local Multidirectional Filtering

1. Defining Crack Indicator Function with Multidirectional Local Directional Filtering

Exploring in depth, it can be found that the concept of crack detection in digital image has evolved from a template matching viewpoint [59]. In this paper the oriented crack template has been retrieved by steering a 2nd order Gaussian derivative filter that generates a filter bank pertaining to the oriented local crack templates over steel strip surface. In this paper Hessian matrix based template has been applied for directional filtering. On obtaining the local crack template, generation of ROI evidence estimation has been performed. In major classical approaches, it has been found that there can be discontinuities in the generation of the local structure, and to alleviate it, Supplementary Evidence Filters (SEFs)were introduced. Noticeably, SEFs behave like the local evidence filter by executing two distinct filters, the backwards filter R_b and the forward filterR_f. These filters in conjunction with the Hessian matrix based local evidence detector R_d enable precise filamentous crack region

identification in local neighbourhood of the detection kernel. Mathematically, the filamentous crack region identification is performed using (5).

$$R_d^* = \max_\theta R_d\,((x,y),\theta;\sigma) \tag{5}$$

$$R_d\,((x,y),\theta;\sigma) = r_d\,((x,y),\theta;\sigma).f\,(x,y) \tag{6}$$

$$r_d\,((x,y),\theta;\sigma) = g_{xx}cos^2\theta + g_{yy}Sin^2\theta + g_{xy}\sin 2\theta \tag{7}$$

In (7), the variables g_{xx}, g_{xy}, and g_{yy}signify the values of the Hessian matrix obtained by performing convolution of the pixel intensity with the Gaussian kernel value. Mathematically,

$$\left(g(p;\sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}}\right) \tag{8}$$

On estimating the Hessian matrix, multiple SEFs filters (as discussed above) were introduced based on local evidence identification using following equations.

$$r_{f((x,y);\sigma,\varphi_1)} = r_d\left(x + d\cos(\theta + \varphi_1), y + d\sin(\theta + \varphi_1)\right) \tag{9}$$

$$r_{b((x,y);\,\sigma,\varphi_2)} = r_d\left(x - d\cos\left(\theta + \varphi_2\right), y - d\sin\left(\theta + \varphi_2\right)\right) \tag{10}$$

Now applying equation (6), (9) and (10), the response for each local evidence SEF filter is obtained as

$$R_f\left((x,y),\theta;\sigma\right) = r_{f((x,y);\,\sigma,\varphi_1)} \cdot f(x,y) \tag{11}$$

$$R_b\left((x,y),\theta;\sigma\right) = r_{b((x,y);\,\sigma,\varphi_2)} \cdot f(x,y) \tag{12}$$

On estimating the responses from each SEF filter separately (i.e., $\mathcal{R}_b$ and $\mathcal{R}_f$), a cumulative crack indicator function is derived by superimposing the responses of the detector and the evidence kernels at different scale values.

$$R\,(x,y) = \max_{\theta,\sigma} R_d + \max_{\varphi_1,\sigma} R_f + \max_{\varphi_2,\sigma} R_b \tag{13}$$

Equation (13) signifies the enhanced local (multidirectional) directional filter that possesses better efficacy as compared to the classical Tubular Flow Field based crack detection paradigms. To augment overall performance, a set of oriented evidence filters were applied for each direction of the detector kernel that enables swift and precise crack detection in multiple directions. This mechanism enables filamentous crack branches as well as root point identification over steel-strip surfaces.

D. Enhanced NFF based Filamentous Crack Segmentation over Steel-Strip Surface

Upon identifying the local crack indicator function, crack-region segmentation was performed using level set approach [60]. Noticeably, in this research level set algorithm has been applied as it enables accurate geometric curve motion estimation even under varying contour region or allied physical (natural) crack topology. To arrive at this objective, an embedding function $\emptyset(x,y,t)$ was derived in such manner that the contour $C(x,y)$ could be presented in terms of the zero level sets of $\emptyset$ at certain instant t. Solving equation (1), we get (14):

$$\varepsilon(\emptyset) = \varepsilon_{reg}(\emptyset) + \varepsilon_{evolve}(\emptyset) \tag{14}$$

$$\varepsilon_{reg}(\emptyset) = v_1 \int_{\Omega} \left|\nabla\emptyset\,(x,y)\right| \delta_\epsilon(\emptyset) d_x d_y \tag{15}$$

$$\varepsilon_{evolve}(\emptyset) = -\int_{\Omega} \sum_{i=1}^{d} \alpha_i\,(x,y)\langle D_i\,(x,y), n(x,y)\rangle 2\,H_\epsilon\,(\emptyset) d_x d_y \tag{16}$$

$$\frac{\partial\emptyset(x,y,t)}{\partial t} = R(x,y)\left(\langle V_1, -\frac{\nabla\emptyset}{|\nabla\emptyset|}\rangle^2 + \langle V_2, -\frac{\nabla\emptyset}{|\nabla\emptyset|}\rangle^2\right)|\nabla\emptyset| \tag{17}$$

Now, observing the expression derived in (14), to perform crack detection an energy-function was derived such that it augments the (filamentous) curve propagation in the naturally crack lined region, excluding the crack-like background components. This makes the proposed system more advanced and robust to meet online and real-time filamentous crack detection in manufacturing setup as well as in pre-established steel-strip infrastructures. In the proposed model following the suggestions in [61], the ROI detection has been performed by reducing derived energy function, i. e objective function $\varepsilon(\emptyset)$ which is mathematically derived as (15).As per equation (16), the defined energy function (ε_{reg}), whose regularizing component limits the length of the original zero level set curve $\emptyset$ signifies the smoothness of the curve. Noticeably, the parameter ε signifies the curve evolution. In (16), selection of the positive factor v_1 helps achieving smoothness of the zero level set $\emptyset$. Here, the smaller value of v_1 provides relatively minute sized or smaller and disjoint

detected crack regions identification in eventual solution. The presence of the vector as defined in (18), signifies the inwards perpendicular unit vector against zero level set curve $\emptyset$. On the other hand, the operating rule $\langle .,. \rangle$ which is mathematically stated as the Euclidean inner product of the functional operator (17).

$$n(x,y) = \frac{\nabla\emptyset(x,y)}{|\nabla\emptyset(x,y)|} \tag{18}$$

In equation (17), the weighting factor $\alpha_i(x,y)$ helps in retrieving the orthogonal and axial component of the proposed NFF model for filamentous crack detection over steel-strip surface (during curve evolution).

As defined and derived in the above section, $\varepsilon_{reg}(\emptyset)$ signifies the force caused due to the regularization energy, while $\varepsilon_{evolve}(\emptyset)$ states the force due to the evolution energy function. As these forces (i.e., $\varepsilon_{reg}(\emptyset)$ and $\varepsilon_{evolve}(\emptyset)$) have already been estimated using Euler-Lagrange method, realizing the need of a robust and automated crack region segmentation model in addition to the ε_{reg} and ε_{evolve} forces a supplementary force was used called local attraction force ε_{attr}. Thus, to enable the proposed model efficient for automated segmentation, a multiple parameters based objective function was derived to be used in level set method. The detailed discussion of ε_{attr} force estimation is given as follows:

E. Local Attraction Force Field (LAF) design

As defined in the above expression, ε_{attr} primarily functions for accommodating the signal intensity variation or losses across the connected filamentous-branches. Typically, there existed signal attenuation causing unexpected discontinuity in the filamentous crack region and eventual turning into disjoint-crack. Furthermore, it can also result in discontinuity especially at the junction points of the neural-branches or at the noisy regions. In such condition, the classical approaches as derived in (15), are insufficient to assure optimal crack segmentation. To alleviate such issues, the use of a Local Attraction Force (LAF) can be of utmost significance. Practically, developing LAF needs precise assessment of the connected components at each time epoch of the level set propagation. At certain point t, to perform evolution of the level set function $\emptyset(x,y,t)$, the set of connected component $C(t)$ can be obtained using (19).

(14)

$$C(t) = H(\emptyset(x, y, t)) \tag{19}$$

In (19),

$$H(z) = \begin{cases} 1 & for\ z \geq 0 \\ 0 & z < 0 \end{cases} \tag{20}$$

Noticeably, in (19), the set of connected components $C(t) = \{c_1, c_2, \ldots, c_p\}$ signifies the binary segmentation at certain time t that encompasses $p \geq 1$ disjoint connected components. It should be noted that the binarization avoids any classical segmentation measure as the binary component itself are retrieved by means of extraction of the interior of the zero level sets of ϕ. Here, the individual disjoint component c_j states a potential candidate with the ability to attract the remaining component c_k (i.e., neighboring disjoint component), where $k \neq j\ (j, k = 1, 2, \ldots, p)$. The predominant purpose of attraction force is to assist contour propagation surface so as to connect itself to the neighboring or local disjoint components.

Considering the practical (complex) scenario, it is not inevitable that all the points on the connected component would be the potential candidates for constituting the attraction force due to the reason that in most of the prevalent discontinuities, minimally one of the two disconnected components or fragments are supposed to be connected by means of boundary points signifying the region of high curvature. The boundary of a component c_j was presented in terms of δc_j, to assist a parent to attract a child, it becomes inevitable to model an attraction field generated through a set of candidate points existing on the boundary of the parent. Thus, for a parent component c_j, point $y \in \delta c_j$ pertains to the potential candidate set if y states a point the convex hull [62], H_j of c_j. In this manner, the potential candidate point-set M_j for c_j can be defined using (21).

$$M_j = \left\{ y \in \delta c_j : \exists x_j \in H_j\ \ s.d.\ \left\| y - x_j \right\|_2 \leq \Delta \right\} \tag{21}$$

In (21), Δ states the positive factor encompassing local boundary coordinates of the neighbouring points on H_j.

The potential (candidate) set of points for a parent component is accountable for retrieving the force sufficient enough to attract the candidate children towards it so as to achieve significant margin for accurate segmentation. The attraction field vectors move towards the ROI, which is nothing else but the (parent) candidate point set. To achieve it (i.e., LAF), vector field convolution (VFC) scheme [63] seems a potential method. VFC model that generates expected external force by convolving the vector field with the object edge map with the ability to attract a contour to the ROI. Mathematically,

$$K(p) = -m(p)\frac{p}{\|p\|} \tag{22}$$

$$m(p) = \exp\left(-\frac{\|p\|^2}{\gamma^2}\right) \tag{23}$$

In (22), $p = 0$ signifies the kernel center. The variable γ states a parameter controlling the capture range of VFC. Considering thin crack presence over steel strip surface, γ was used that exists in the range of 0.2×10^{-6} to 1.5×10^{-6} meter. Noticeably,

In the proposed model the optimal set of points M_j specially functions as ROI for the parent c_j towards which the other components are supposed to be attracted. On performing convolution of the kernel and the candidate set, a vector field was retrieved in which vector components are directed towards the parent and their quantitative value (say, magnitude) attenuates slowly as per increase in distance from the candidate set. Assuming that the points in (21) (i.e., in M_j) are 1, then for $E_j(x)$, the binary edge map, it becomes feasible to estimate LAF field (24).

$$\Gamma_j(x) = E_j(x) * K(x), \ \ \forall A \in \Omega \tag{24}$$

After obtaining the attraction field, it becomes possible to constrain a locality by means of avoiding remote components. Furthermore, this method allows automated segmentation without human interference, which is not available in classical morphological based crack detection approaches. The proposed LAF model functions for attracting local connected components present in the vicinity of the parent's boundary convexity. Estimating $\Gamma_j(x)$ for parent set (c_i) and child set (c_j), the parent set attracts the child with a force LAF, which is mathematically derived as (25).

$$F_{attr}^{(i,j)}(z) = k_i \langle \Gamma_j(z), -n(z) \rangle \theta_j(z) \tag{25}$$

In (25) the indicator function $\theta_j(z) = 1$ when $z \in \delta c_j$, otherwise $\theta_j(z) = 0$. The variable k_i states the normalized quantifiable value (say, mass) of c_i, which has been estimated as the ratio of the number of pixels/voxels in c_i to the total pixels/voxels in $\{c_1, c_2, \ldots, c_p\}$. Using k_i the proposed model enables heavier connected components to have more attracting power. Assuming that the filamentous curves possess larger volume as compared to the noisy steel strip surface, the solution of the level set function was alleviated by exhibiting "Area-opening function" that removes small and insignificant components having total area smaller than the threshold value. Thus, total attraction force F_{attr} for each parent-child pair was estimated. Mathematically,

$$F_{attr}(z) = v_2 \sum_{i=1}^{p} \sum_{j \neq i}^{p} F_{attr}^{(i,j)}(z), \ \ \forall A \in \Omega \tag{26}$$

In (26), v_2 which is a positive scalar vector ranging [0-0.02] estimates the overall influence of attraction force on the curve evolution. On estimating the attractive force, it becomes easy to initiate level set method that intends to reduce an objective function for active contour propagation and automatic crack segmentation over steel strip surface. Adding LAF as an objective function, (15) is augmented as (27).

F. Level Set Evolution and Objective Function Minimization

The objective function can be minimized by means of certain variation calculus approach. In this relation, in addition to the objective function components as mentioned in (15), LAF $\varepsilon_{attr}(\emptyset)$, was introduced thus making overall objective function as (27).

$$\varepsilon(\emptyset) = \varepsilon_{reg}(\emptyset) + \varepsilon_{evolve}(\emptyset) + \varepsilon_{attr}(\emptyset) \qquad (27)$$

Noticeably, the prime significance of LAF is that it helps in enabling propagation of the contour surface for attaching itself to the disjoint crack segments automatically and precisely, without constraining human interference and allied inaccuracy. Now, considering the Gateau's variation of the LHS of (27), (i.e.,$\varepsilon(\emptyset)$) in conjunction with $\emptyset$, to achieve (28)

$$\frac{\delta\varepsilon}{\delta\emptyset} = \frac{\delta\varepsilon_{reg}}{\delta\emptyset} + \frac{\delta\varepsilon_{evolve}}{\delta\emptyset} + \frac{\delta\varepsilon_{attr}}{\delta\emptyset} \qquad (28)$$

In the proposed method, in (28), the variable $\emptyset$ is updated iteratively using Gradient Descent (GD) algorithm. In other words, assigning $\frac{\delta\varepsilon}{\delta\emptyset} = -\frac{\delta\emptyset}{\delta t}$ where t signifies the pseudo time parameter for iterative update. Mathematically,

$$\frac{\delta\emptyset}{\delta t} = \varepsilon_{reg}(x) + \varepsilon_{evolve}(x) + \varepsilon_{attr}(x) \qquad (29)$$

Once estimating (26), the derived outcome of (29) enables iterative computation of the level set function (30).

$$\emptyset^{k+1} = \emptyset^{(k)} + \Delta t \mathcal{L}^{(k)} \qquad (30)$$

To enable stable computation smaller value (approximately 0.1) of Δt was considered. The parameter $\mathcal{L}^{(k)}$ states the discretized form of the output of (29) and the level set function at instant k is given by $\emptyset^{(k)}$. To perform filamentous crack detection, it is important to initiate an active contour while assuring that the initiated curve exists within the filamentous crack region. Though, manually it can be done by clicking within the crack region, classical approach was avoided and follow a global thresholding method applying Otsu's method [64] that in conjunction with "Area-opening function" performs noisy binary segment removal. This iterative process is stopped upon identifying that there is no significant change in the length of the zero level curve of $\emptyset$. Thus, once convergence is achieved, the filamentous structure (detected crack region) is extracted by performing selection of the largest binary component in the solution. It is then followed by fitting a cubic spline to each detected crack (branch) so as to enable smooth tracing of filamentous crack centerline. The proposed crack detection method has been tested with both academic benchmark data retrieved from North-Eastern University (NEU) as well as primary data collected from Industries. The discussion of the achieved results and its inferences is given in the sub-sequent section.

V. RESULTS AND DISCUSSION

In this paper the predominant emphasis is made on developing a novel steel strip crack detection system. Unlike classical approaches such as Eddy current based approach, magnetic field based approaches or even classical segmentation paradigms, this paper focuses on designing a novel and robust neural segmentation paradigm that could be of vital significance for "filamentous crack detection", which is commonly caused due to fatigue or strokes within manufacturing set-up or during application. Over the last few years, vision based approaches have been developed for crack detection; however, majority of the existing methods apply classical morphological features based segmentation with certain predefined threshold value. The efficacy of such approaches often remains limited, especially for the "thin" and "filamentous" crack. The topological characteristics of the filamentous crack on steel surface can be non-uniform and varying across all branches (neural branches). In this approach the classical crack segmentation methods can't be effective. Though a few approaches such as wavelet transform, watershed transform etc have been applied to perform crack detection; however, these approaches could not address the issue of thin-filamentous crack detection over steel strips. The prime reason behind such limitation was its strict dependency on connected component based crack detection and morphological uniformity. Unlike the classical approaches this paper presents a novel and robust Varying-Morphological Segmentation (VMS) model or Neuron-Model Segmentation (NMS) scheme that exploits Contour Propagation assisted Local Feature Extraction (LFE) to enable accurate crack detection over steel strip surface. Being a vision based crack detection paradigm the proposed method is developed based on the principle of template matching where an oriented filamentous crack template is obtained by performing multi-directional filtering assisted 2nd order Gaussian derivative filter (steering) so as to generate a filter bank of oriented local crack templates. In this paper a Hessian matrix based template was generated as reference template, which was then processed for local feature extraction and local template matching across the image to perform filamentous crack region identification. On generating the local crack template, the overall image was filtered to segment the complete crack region. The proposed method comprises multiple steps to perform filamentous crack segmentation. The first phase of implementation executes crack indicator function that identifies the presence of a steel strip crack at each location of the digital image. The second phase executes the multidirectional contour propagation to obtain the LFE for segmenting the overall filamentous crack region. The emphasis is made on reconstructing filamentous (neuron structure) crack region from the steel strip's surface image. The proposed VMS model was first augmented to perform filamentous crack region identification from the noisy input image. It was then armored to deal with the local structural discontinuities resulting from local-noisy environment and clutter conditions. To deal with such issues, our proposed VMS model was derived by means of a variational framework driven by level sets. Here, our applied level set concept was designed in such way that it intends to minimize an energy-function $\varepsilon(\emptyset), where\ \varepsilon(\emptyset) = \varepsilon_{reg}(\emptyset) + \varepsilon_{evolve}(\emptyset) + \varepsilon_{attr}(\emptyset)$. We designed an enhanced Non-linear (Tubularity) Flow Field concept (NFF) by exploiting local filamentous crack or neuritis features. Consequently, it helped in performing segmentation by executing curve evolution along the axis and thickness of the filamentous crack or neuritis.

One of the key novelties of our proposed crack detection method is the consideration of a local attraction force that enabled accommodation of the intensity variations in the filamentous crack region or neural structure. This method enabled developing a unified and automatic model to connect the naturally allied components (i.e., components of the crack region). Unlike classical region-growing approaches based segmentation, our method avoided any user-defined seed-point introduction and thus found potential as an automatic crack detection system. Furthermore, it also avoids any sophisticated post-segmentation analysis task such as connected component analysis (CCA) like Watershed transform and therefore is computational more efficient than other state-of-art techniques. Our proposed method enabled connecting the disconnected component, despite its low signal intensity that eventually enabled precise and reliable crack region identification and segmentation at fine-grained (minute) level. Noticeably, the inclusion of local attraction force in level set paradigm (25) enabled it to achieve automated steel strip (filamentous) crack region segmentation.

The following discussions represent the visual performance assessment by our proposed system for steel strip surface crack detection. Here, the performance of the proposed crack detection system was demonstrated with multiple crack topology and allied complexity. Noticeably, to make implementation efficient visual images of same size have been considered. To assess performance, the standard datasets named North-Eastern University (NEU) surface defect dataset [65] was taken into consideration. The datasets of NEU are of similar size (i.e., 200x200 pixels). Noticeably, NEU dataset comprises surface defect dataset with six types of surface defects of the hot-rolled steel strip. There are six distinct types of defects rolled-in scale (RS), patches (Pa), crazing (Cr), pitted surface (PS), inclusion (In) and scratches (Sc) and crack. This dataset comprises of 1800 gray scale images with 300 images for each type of defect. Some of the samples of the NEU steel strip surface defect dataset for each defect category is given in Fig 2. Considering the NEU dataset it can be easily visualized that the inter-class defect datasets possess significantly- large differences in appearance, while inter-class surface defects data (i.e., surface images) have similar aspects but with varied illumination, shadow and allied material differences. Undeniably, the classical crack segmentation approaches can identify crack region if it is straight and all components are closely connected; however, their efficiency gets confined in case of cracks with multiple branches with varying (signal) intensity and non-linearity.

Considering this, the performance for both steel strips was evaluated with single crack as well as with multiple cracks and varying intensity. In this study, to get real time crack steel-strip data, samples were collected from JSW Steel Ltd, Vijayanagar works, India. It is a matter of fact that the width of steel-strip crack used to be very thin and therefore those images were considered in which the widths of cracks vary in the range of 1-5 pixels. To assess robustness of the proposed steel strip crack segmentation model, the images with sharp branch variations has been taken into consideration where the presence of very thin cracks forces the (crack) detection model to perform optimally. A snippet of the input data, and eventual crack-detected images are given in Fig 3. Noticeably, to enable better perceptibility images have been zoomed after processing. Observing these results, it can be easily visualized that the proposed system is capable of performing crack-detection with different topology and varying illumination or local cluster conditions.

VI. CONCLUSION

In this paper, a highly robust vision based steel strip surface crack detection system has been developed. Unlike

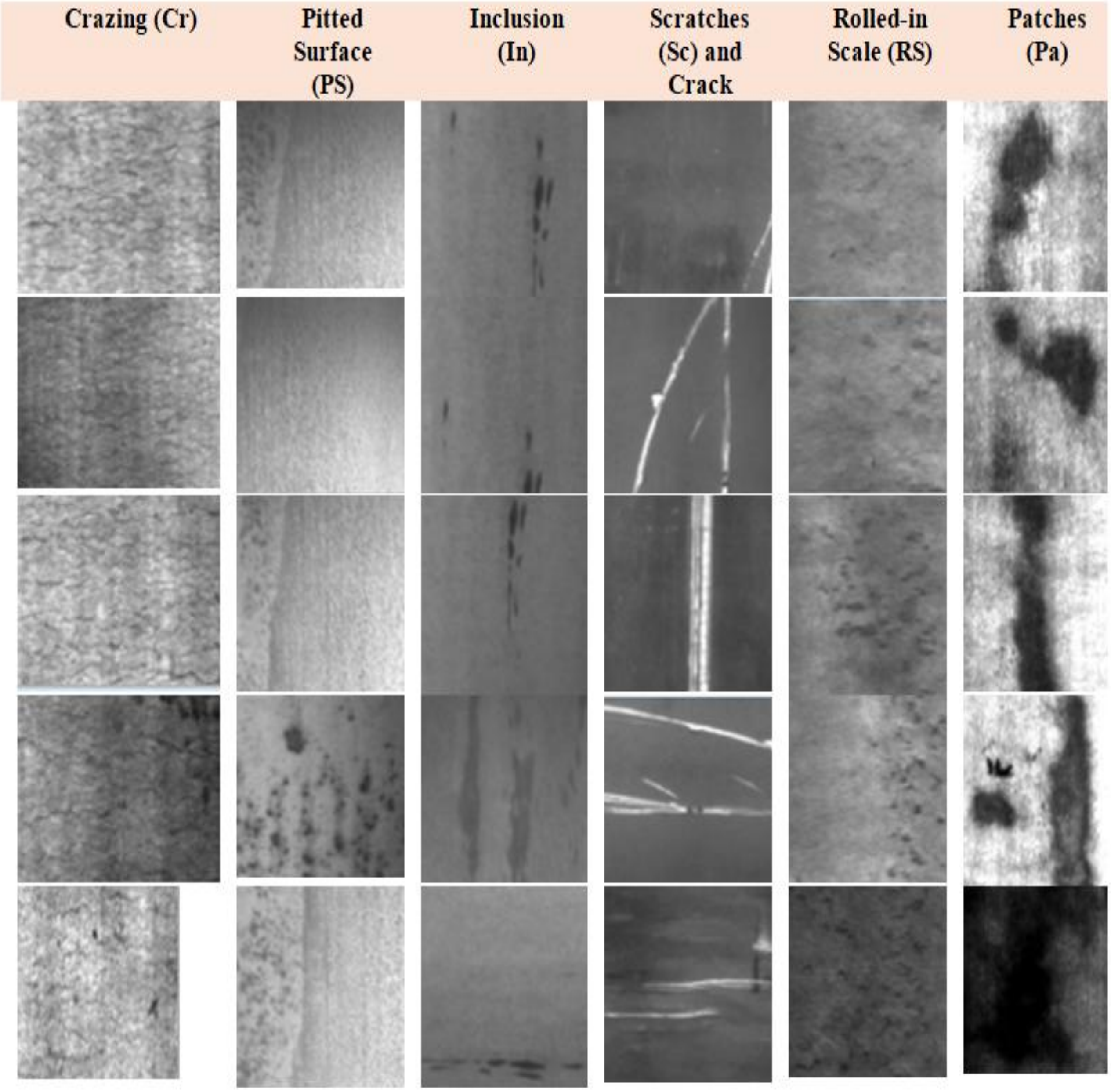

Fig. 2. Samples of NEU Surface crack dataset (*Source: http://faculty.neu.edu.cn/yunhyan/NEU_surface_defect_database.html)

classical straight line crack identification schemes, the proposed model focuses on efficient crack detection especially for filamentous type of steel-strip surface crack, which is normally caused during production and in-functional operation due to strokes, strain or fatigue. Further, the focus was also on developing an automatic crack detection scheme. The use of Varying-Morphological Segmentation (VMS) also called Neuron-Model Segmentation (NMS) has played decisive role. The proposed VMS model in conjunction with active Contour Propagation and multi-directional filters based Local Feature Extraction (LFE) enabled realization of a variational framework driven by level sets that intend to minimize an energy-function signifying summation of regularization energy, evolution energy and a robust local attraction force. This approach enabled the proposed crack detection scheme to be automatic. Unlike classical region growing based approaches where user needs specifying (initial) seed-point, the proposed scheme applied a robust local attraction force that with help of local Otsu threshold method enabled automatic filamentous crack detection over steel strip surface. One of the noticeable novelties of the proposed crack detection method is that it avoids any sophisticated post-segmentation analysis like connected component analysis (CCA).

A simulation result with standard benchmark data as well as first-hand collected data has revealed that the proposed system exhibits satisfactory performance for steel strip surface crack detection irrespective of its (crack region) topology or illumination condition. The results could be assessed only in terms of segmentation outputs. In future, the focus should be made on enabling segmentation followed by surface defects classification to make real-time decisions.

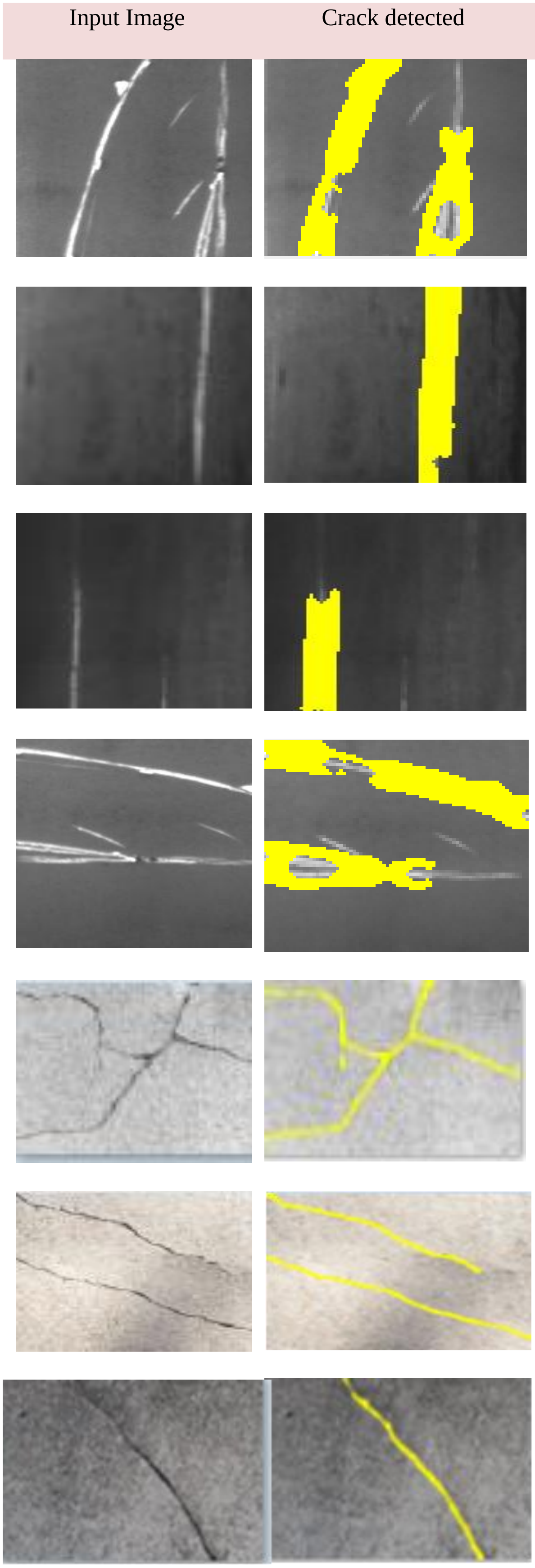

Fig.3 Simulation Results

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