Post processing algorithms for distributed optical fiber sensing in SHM applications

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Abstract: Distributed Optical Fiber Sensors (DOFS) are measuring tools whose potential related to the civil engineering field has been discovered in the latest years only (reduced dimensions, easy installation process, lower installation costs, elevated reading accuracy and distributed monitoring). Yet, what appears clear from numerous in-situ DOFS monitoring campaigns (bridges and historical structures among others) and laboratory confined experiments, is that OFS monitorings have a tendency of including in their outputs a certain amount of anomalistic readings (out of scale and unreliable measurements). These can be both punctual in nature and spread over all the monitoring duration. Their presence strongly affects the results both altering the data in its affected sections and distorting the overall trend of the strain evolution profiles; thus the importance of detecting, eliminating and substituting them with correct values. Being this issue intrinsic in the raw output data of the monitoring tool itself, its only solution is a computer-aided post-processing of the strain data. The present paper discusses different simple algorithms for getting rid of such disruptive anomalies by means of two methods previously used in literature and a novel polynomial based one with different levels of sophistication and accuracy. The viability and performance of each is tested on two study case scenarios; an experimental laboratory test on two reinforced concrete tensile elements and an in-situ tunnel monitoring campaign. The outcome of such analysis will provide the reader with both clear indications on how to purge a DOFS-extracted data set of all anomalies and on which is the best suited method according to their needs. This marriage of computer technology and cutting edge Structural Health Monitoring tool not only elevates the DOFS viability but provides civil and infrastructures engineers a reliable tool to perform

previously unreachable levels of accuracy and extension monitoring coverage.

NOTATION TABLE

Notation	Definition
SHM	Structural Health Monitoring
OFS	Optical Fiber Sensor
DOFS	Distributed Optical Fiber Sensor
OBR	Optical Backscatter Reflectometer
RC	Reinforced Concrete
SRA	Strain Reading Anomaly
HL-SRA	Harmless Strain Reading Anomaly
HF-SRA	Harmful Strain Reading Anomaly
SSQ	Spectral Shift Quality
GTM	Geometrical Threshold Method
PICM	Polynomial Interpolation Comparison Method

1 INTRODUCTION

As clearly stated by Brownjohn¹, civil infrastructure provides the means for a society to function. The wide range of applications that civil engineering offers includes buildings, bridges, highways, tunnels, power plants, industrial facilities, geotechnical and hydraulic structures among others. Each of these is subjected to multiple events that deteriorate and compromise its structural integrity in a unique way throughout its service lifetime exposing its future performance to several risks. In order to avoid the social, economic and environmental costs of deterioration and/or failure, civil structures have different safety and durability requirements that need to be met and that ensure a correct structural performance and the wellbeing of their

users. For that, a series of inspection, monitoring and maintenance protocols have to be carried out during the structure's service lifetime.

The effectiveness of these monitoring methods relies in their ability to rapidly detect alterations on the structure's performance, allowing for its identification, characterization and control. This idea is the basis of *Structural Health Management* (SHM), which, according to Housner et al.², can be understood as the continuous or regular measurement and analysis of key structural and environmental parameters under operating conditions, for the purpose of warning of abnormal states or accidents at an early stage.

Traditional structural monitoring techniques involve the use of inclinometers, accelerometers, extensometers, total station surveys, load cells and GNS-based sensors, among many others. These tools have a wide applicability and are quite reliable since their correct deployment is widely acknowledged, easily ensuring reliable monitoring and, consequently, structural assessment. However, as stated in Baker³, conventional forms of inspection and monitoring are only as good as their ability to uncover potential issues in a timely manner. Regarding the ability of damage detection, traditional tools present several drawbacks such as insufficient data management ability, the need for the infrastructure's service interruption during their deployment, non-automated real-time measures and non-distributed sensing and more.

Among the most modern monitoring technologies adopted in the structural engineering field, Optical Fiber Sensors (OFS), SOFO deformation sensors⁴, Global Positioning Systems (GPS), radars, Micro Electro Mechanical Systems (MEMS) and Image Processing Techniques are increasingly gaining in popularity. As a matter of fact, these have opened the doors to the extraction of structural information that could not be acquired before^{5,6}.

Generally speaking, the structural assessments through monitoring tools rely essentially on the precision of the sensors, on its automation level and data management speed. OFS sensors have recently upped their performance to embrace these requirements and are the main subject of the present paper. These sensing tools provide several advantages regarding SHM given its reduced dimensions, easy installation process, lower maintenance, lower installation costs, reading accuracy, immunity to electromagnetic influences and aggressive environments. The fundamental principle behind OFS is the propagation of light through an optical fiber cable (diameter of 125 μ m) whose core is usually composed by silica (SiO₂) and is protected by an external polymer-type cladding. These can further be protected by an extra coating layer despite the present paper displays results extracted with strictly bare OFSs. The light travelling through the core is a monochromatic laser and moves forwards in the fiber thanks to internal reflections. When light is travelling in the optically dense medium that is the core and strikes a

boundary at a particular angle (larger than the critical angle of the boundary), the light experiences total internal reflection and is, therefore, confined in the core. Any variation that the structural surface is subject to is reproduced in the fiber (bonded on it) causing a physical modification/perturbation in its optical core. These perturbations can be detected thanks to light scattering; a phenomenon that naturally occurs whenever the light beams' photons interact with the core's inhomogeneities generating a second magnetic wave (scattering or return) that heads back towards the light source (backscattering)⁷. The main back-scattered spectral components include Raman, Brillouin and Rayleigh. These are measured to identify strain and temperature variations.

OFS can be categorized into three different groups: grating-based sensors, interferometric sensors and distributed sensors. Most OFSs, such as Fiber Bragg Grating sensors (FBG)⁸ or Fabry-Perot sensors⁹, are discrete and can only provide local measurements thus potentially omitting important information in structural areas that are not explicitly instrumented. Furthermore, analyzing a structure's global behavior by means of discrete sensors would require the installation of a high number of sensors producing a dense system of monitored points, which translates into a difficult and expensive deployment and complex data acquisition. *Distributed Optical Fiber Sensors* (DOFS) were developed to deal with these limitations allowing for a distributed monitoring of strain and temperature along the entire optical fiber length by means of a single cable between the sensing fiber and the reading device. There are several sensing technologies based on DOFS: *Raman Optical Time-Domain Reflectometer* (OTDR), *Brillouin Optical Time Domain Reflectometer* (BOTDR), *Brillouin Optical Time Domain Analysis* (BOTDA), *Optical Frequency Domain Reflectometry* (OFDR), *Optical Backscatter Reflectometer* (OBR), among others. These are characterized by different sensing ranges and spatial resolutions which makes them suitable for different deployments. In particular, the OBR technique used in the applications presented in this paper is a *Rayleigh Backscattering based Optical Backscatter Reflectometer* (OBR). It provides a good cost-efficiency balance granting millimetric spatial resolutions at the expense of low sensing range (only up to 70m¹⁰).

DOFS have been implemented in both laboratory structural engineering experimental campaigns^{7,11,12} and in real structural applications such as dams^{7,8}, high rise buildings¹³, bridges^{10,14}, slopes¹⁵, piles¹⁶ and pipelines¹⁷ among others. However, given it is a new/under research technology it still presents some limitations. To start its elevated initial investment cost makes it a very selective monitoring technique, the frequent appearance of anomalies in the readings, the lack of reliable fiber-structure bonding techniques and the lack of standardized guidelines that ensure success in every deployment.

The frequent appearance of anomalies in the strain measurements in the form of abnormally high peaks that distort the strain profiles is the topic of the present article. In our case, the article is aimed at proposing various numerical-computing assisted methods for the identification and treatment of such anomalous readings both novel and from the literature. The Spectral Shift Quality method and Geometrical Threshold Method are part of the latter category while the Polynomial Interpolation Comparison Method is introduced for the first time in the present article. Their efficiency is tested on two study case scenarios; an experimental laboratory campaign on two Reinforced Concrete (RC) tensile elements (ties) and a real life in-situ monitoring campaign of the inner surface of a lining-formed metro tunnel in Barcelona. The results will testify the efficiency of the novel methodology over the more commonly used ones despite confirming the viability of the latter for a fast preliminary analysis.

2 STRAIN READING ANOMALIES

Figure 1 below exemplifies the possible outputs of a strain monitoring experimental campaign performed with the use of DOFS. On the one hand, in Figure 1a the red plot displays the deformation state of a 1.2m long DOFS over its multiple points in the single instance in which the measurement is performed. Such strain readings are assumed equivalent to the one of the monitored surface on which it is bonded but in reality it is a function of the ratio between the stiffness of the latter and the used adhesive. On the other hand, Figure 1b displays the evolution of strains of a single monitoring point of the fiber versus the test time. As visible, the gathered output is provided to the tester as a raw data set with the following components:

- Length vector: representing each sensing point along the fiber (henceforth defined as *DOFS coordinates*) where the measurements have taken place as a function of the selected gauge length and gauge spacing or spatial resolution.
- Strain matrix: comprising the strain readings along the whole fiber for a particular time in each row.
- Time vector: specifying the date and time of the performed measurement.

What is also evident in Figure 1a is the great clarity difference between the red dashed and blue continuous plots. This is due to the post-processing process that the blue curve received in order to remove the visible large strain peaks present in the DOFS raw output. These strain peaks, also present in Figure 1b, are unexpectedly high, punctual in nature and of doubtful meaning henceforth referred to as *Strain Reading Anomalies (SRAs)*.

Many DOFS monitored campaign report such anomalies. In Villalba et al.⁷ the external face of a RC slab was instrumented with DOFS in order to explore the fiber's crack detection ability. Here, large peaks are detected early in the test and are attributed to points of strain concentration due to cracks. As the load increases such peaks degenerates into quasi-infinite peaks, clear SRA identifier. A DOFS monitoring of another RC slab¹⁸ also reports SRAs. In Davis et al.¹¹ the strains inside different RC ties are monitored with the goal of gaining insights into the concrete-reinforcement bond performance of corroded specimens and the detection of pitting corrosion. During the tension of the ties numerous large peaks appear sometimes even deeply in compressive domain which is improbable considering the nature of the tensile test. Another RC tie test developed by the authors also displayed the rise of SRAs with load¹².

Figure 1. DOFS-extracted strains profiles versus DOFS coordinates (a) and versus time (b)

In Barrias et al.¹⁹ the DOFS sensors were, instead, used to monitor the deformations of a RC bending element unloaded and reloaded again to assess the performance of the sensor when applied to a real loading scenarios in concrete structures. Here too, after the development of cracks, high magnitude peaks are observed and later substituted through interpolation with the surrounding values. These issues are also present in other RC beams strain monitoring campaigns^{20,21,22}. Reported in-situ SHM campaigns are also not SRA free²³. These issues don't seem to be isolated to cases with RC though. Indeed, in Bado et al.²⁴ a DOFS monitoring campaign was performed on bending rebars finalized to the analysis on the possible causes of the rise of SRAs. Anomalistic readings were recorded beyond 4000 $\mu\epsilon$ and the authors concluded that, for strains inferior to such level, the most probable cause of such anomalistic behavior is the concrete's friction (especially when cracked) against the fiber.

Another possible reason for the appearance of such anomalies is offered in Ding et al.²⁵, suggesting that they are caused by a localized failure of the algorithm that tracks the light impulses through the range length under analysis and during a particular wavelength sweep. Finally, it should be noted that some deployments of DOFS sees the fiber being bonded to or with highly heterogeneous materials (for example, concrete), whose structural discontinuities (joints, cracks, corners, etc.) may significantly affect the readings.

Generally talking, a strain peak at a DOFS coordinate x_k is usually considered as an abnormal reading if it presents a large difference with previous reading at coordinate x_{k-1} . This is valid both in terms of time and space (time vector and

length vector). Temporally speaking, two consecutive measurements should present similar strain readings when the time interval between them, and thus their load difference, is almost negligible. Spatially wise, if to consider that the resolution of both experimental tests ranges between 5 and 10mm, strains simply hardly peak in neighboring sections without a certain amount of lead-up gradual growth. In some cases, opposite strain peaks in tension and compression are reported in two neighboring readings which is once again illogical given the short distances between the two consecutive and theoretically similarly behaving sections. A reading can be considered abnormal if large tensile peaks appear in theoretically fully compressed area of the structure or the other way around. All these reasons suggest that these anomalies are reading errors from the DOFS, fact that is confirmed in various experimental campaigns^{19,24} that complemented the DOFS-monitoring with other monitoring tools (strain gauges) and theoretical models, which did not explain nor present the peaks read by the DOFS.

In Bado et al.²⁴ two types of strain-reading anomalies are identified, harmful and harmless SRAs. The first, *Harmless Anomalies* (HL-SRAs) are those strain peaks that, while preventing the correct reading of the strains at a specific time, still allows it in later instances. Being the nature of this anomaly punctual in nature (see Figure 2), it is easily identifiable in the strain profile of a section as an excessively large and punctual peak surrounded by coherent strain readings. *Harmful Anomalies* (HF-SRAs), are those strain peaks that are followed strictly by additional anomalistic readings.

Figure 2. Graphical representation of different SRAs' theoretical definitions

Hence, from their initial appearance and for the rest of the monitoring period, all the measurements are considered unreliable. Figure 2 compares the looks of a DOFS reading when affected by a HF-SRA at DOFS coordinate x_k against its neighboring sections (x_{k-1} and x_{k+1}). Note that this kind of anomalies might be “contagious”, meaning that the surroundings of an identified HF anomaly might become, in posterior times, an HF-SRA itself.

SRAs, combined with a lack of a universal reliable DOFS/structural support bonding technique, limit DOFS from becoming a reliable universal strain-reading tool. As a result, SRAs prevent accurate and reliable readings (in a specific location or along time), extensively increase the level of unreliability of the surrounding measurements and distort the global and/or local strain trends. In any DOFS-monitored campaign these are crucial undermining factors which may lead to the actual discarding of such technique. Thus SRAs should be avoided entirely and, if that isn't possible, deleted in the data post-processing phase.

In order to identify all the anomalies in the readings, the trend of every sensing DOFS section has to be studied and each single anomalistic peak manually corrected and/or removed. Such a tedious analysis may not actually be viable in many projects considering factors such as large dimensions of the data sets due to wide extensions of monitoring surfaces or long monitoring periods, time-limitations, financial constraints, lack of qualified personnel and more.

With an essential contribution from computer technology these issues can be tackled finally making DOFS a viable performant option for any Structural Health Monitoring campaign. Consequently, the need to develop an algorithm that automatizes this process to the maximum extent possible. The present paper proposes a post-processing method aimed at achieving just that. In the following chapters the logical process of the algorithm will first be explained and later tested on the readings obtained in two study case scenarios.

3 STUDY CASE SCENARIOS

This paper analyses the results of two different DOFS-monitored deployments. The first is a structural laboratory experimental campaign while the second is a real-life application in a metro tunnel in Barcelona (Spain). In both cases the monitoring was performed by means of an ODISI-A (Optical Distributed Sensor Interrogator) OBR (Optical Backscatter Reflectometer) manufactured by LUNA Technologies²⁶. The ODISI-A uses swept-wavelength

coherent interferometry to measure temperature and strains. It offers the possibility to test a structure wholly or in the chosen points of interest with user-configurable sensing resolution and gauge lengths.

The laboratory experiment saw the DOFS instrumenting of two RC ties named 12x12_D12.01 and 12x12_D12.02. The first part is indicative of the cross-sectional dimension of the RC tie (in our case 12cm tall and 12cm wide) whilst the digits following the letter D are representative of the rebar diameter (12mm). Their longitudinal dimensions are, instead, displayed in Figure 3a. Whilst member 12x12_D12.01 is constituted of a single prism, 12x12_D12.02 is constituted of two concrete prisms that act completely independently due to the tensile nature of the test itself. Thus, by means of the resulting uniform distribution of stresses along the rebar during such test, this layout allows the simultaneous but separate study of two RC ties. The averaged concrete's compressive strength is equals to $f_{cm}=39.5\text{MPa}$, its tensile strength to $f_{ctm}=3.1\text{MPa}$ whilst the two modulus of elasticity are $E_{cm}=32.8\text{GPa}$ for concrete and $E_{sm}=200.4\text{GPa}$ for steel. The DOFS is bonded to the steel rebars in order to constantly monitor its strains when subjected to monotonic tensile load through a Universal Testing Machine (UTM) at a constant loading speed of 0.1mm/min. The 1.2m long fibers measured the steel's strains with a spatial resolution of 5mm and 7.5mm and were bonded to them with cyanoacrylate (CYN) adhesive only after it was positioned in a longitudinal groove that was previously incised along the bar's rib as in Figure 3b.

Figure 3. Study case RC ties (a) with dimensional and DOFS bonding characterization (b)

Figure 1 above displayed two DOFS strain measurements extracted by the first of these two RC ties. As visible, despite considering just one strain-DOFS coordinates and one strain-time plot, numerous anomalies are already visible requiring a hefty hand of post-processing.

(a)

(b)

(c)

Figure 4. Tunnel DOFS installation (a), picture of the DOFS coordinates $\sim 45.50\text{m}$ (b) and picture of DOFS coordinates from $\sim 20\text{-}26\text{m}$ (c)

The in-situ DOFS deployment consisted in the monitoring of the strains in Barcelona's L9 Metro Sagrera TAV-Gorg metro tunnels' inner surface whose structural performance could have been potentially affected by a residential building being constructed on top and slightly covering its layout. COTCA S.A. proposed a DOFS deployment in order to perform a continuous follow-up of the tunnel's strain and tensional states during the excavation and construction works happening 14.40m above the tunnel's keystone.

The monitoring scheme involved the installation of a 50m long DOFS bonded to the concrete lining's inner surface (Figure 4) by means of epoxy resin after a previous superficial preparation of the concrete lining that consisted of, firstly, refining the surface's existing irregularities with sandpaper and, later, applying rubbing alcohol and special products to avoid grease, air humidity and direct moisture.

Obviously, as with any real world application scenario the installation conditions weren't the best and the presence of physical discontinuities could not be avoided. These limitations might lead to a wide range of anomalies in the readings which emphasizes the need for an appropriate post-processing technique. The DOFS setup provided strain readings with a spatial resolution of 10mm and was installed along the supposedly most affected tunnel section, i.e. the one found right below the construction site. Figure 4 shows how, starting from the end, the fiber covers a complete transversal section (coordinates 50.00m-23.00m), followed by a longitudinal monitoring segment (23.00m-14.24m) and ending in a partial transversal section coverage (14.24m-

10.00m). The remaining 10m are not bonded to any structural surface and their main goal is aimed at providing sufficient data to perform a temperature compensation of the strain readings in case of variations during the monitoring period.

Figure 5a presents the OBR strain measurement of a single fiber coordinate at different instances during the construction period (from October to May) in the DOFS coordinates interval between 26 and 40m (for clarity purpose the latter was chosen as it is the most representative of the various kinds of SRA), as well as the delimitation of the structurally differentiable segments that the fiber covers, which, helps understand why some areas present a higher amount of anomalies than others.

Figure 5b expands on Figure 5a by combining in a 3D graph the un-processed DOFS strain measurements collected in an exemplary 40-days span. This figure summarizes the above explained SRAs as it clearly displays how HF-SRAs, after their formation, remain present for the rest of the monitoring campaign and how HL-SRAs quickly appear and disappear. Furthermore, both anomalies can be found in both tension and compression hence the strain peaks can be identified on both sides of the graph.

Figure 5c zooms in Figure 5b in order to display, in combination with Figure 5d, the difference between a HF-SRA and a damage-induced peak where a crack appears (both figures display the strain profiles of a 0.5m long DOFS segment). As mentioned earlier, it is crucial not to confuse the two as the unintentional deletion of the latter would go

against the purpose of the test itself. Granted HF-SRAs are a consistent discontinuity against neighboring data, their appearance due to damage in a RC structure is never perfectly punctual. Oppositely, the presence of a certain amount of strain build-up on both sides of a crack can always be detected. This is evident in Figure 5d which displays a three dimensional view of a DOFS strain monitoring campaign (originally reported in Bado et al.¹²) of a Ø12 steel rebar embedded inside a 100x100mm cross-sectional, 600mm long concrete prism and later tested in tension. In the present figure it is possible to see two successive cracks opening respectively at time 110s around DOFS coordinate 0.755m and time 217s in DOFS coordinate 0.94m. Figure 5d's results are similar to other DOFS monitoring campaigns' performed both on the external surface of a RC member^{7,27} and inside it (DOFS bonded to rebars)^{28,29}. As a matter of fact, in these campaigns the adjacent build-ups can assume the aspect of an inverted nosecone cross-section whose base is as small as 20cm and as large as half a meter. This non-abrupt but relatively gradual rise in strains allows to clearly distinguish the insurgence of a damage in the structure against a HF-SRA.

The significantly different nature of this paper's study case deployments allows for the development of a general and widely applicable post-processing technique on the basis of their collected readings.

4 THE SRAS POST-PROCESSING STEPS

The objective of a post-processing algorithm is to treat the raw strain measurements and obtain a new set of data that is more reliable and as free as possible of any SRAs-induced distortion. Its core process is based on the following logical sequence.

1. *Automatic detection of SRAs* → 2. *Removal of SRAs*
→ 3. *Substitution by interpolation*

The automatic detection of the SRAs is the most crucial part of the process. Being HL-SRAs effectively data outliers, commonly one would label a data as a potential outlier when the latter's standard deviation surpasses by a certain number of folds (usually 2) the mean. Yet, the presence of outliers is likely to have a strong effect on the mean and the standard deviation themselves thus making this technique pragmatically defective. Elsewise, an outlier reading can be considered as any value that is more than three scaled

median absolute deviation (MAD) away from the median value within a sliding window. Still this method wouldn't meet the necessary requirements for detecting an SRA as it wouldn't be able to distinguish an SRA from a strain peak caused by a sudden opening of a crack, impact or load increase effectively removing the data indiscriminately. Furthermore, this method would be unable to detect HF-SRAs due to the proximity of erroneous strain values subsequent to the first anomalous reading. As a matter of fact, no post-processing should be run without a previous thoughtful review of the loading and structural conditions of the case study one is working on. Indeed, being the objective the deletion of unreliable readings that do not reflect the real behavior of the monitored structure, care should be taken in the coherence of the peaks elimination. It should be neither excessive (which would imply a loss of reliable data) nor insufficient (which wouldn't allow for interpretation of readings).

For example, as mentioned earlier, if a laboratory experiment involves the evaluation of a structure under impact loading or up until crack formation, a correct post-processing would have to account for a sudden and high strain variation between consecutive readings. Thus, the tendency of the raw data should be first identified and only later can the peaks elimination pattern be defined.

Just as the strain matrix can be referred to the length vector or the time vector so can the detection of SRAs be performed along space or time. SRAs in space and time are exemplified in Figure 6. Notice that the HL and HF-SRAs displayed in Figure 2 are actually jumps in time. Anomalies in space are usually of the HL kind hence only appear as a single large peak. An abrupt increase of strain magnitude which remains constant thereafter (looking like a HF anomaly) could happen, for example, if a single fiber is used to continuously monitor differently stressed structural surfaces (a beam in bending with the fiber bonded sequentially on the upper and lower surfaces for instance). In the current study cases, though, such condition isn't met as the fiber is uniquely and continuously bonded to a rebar (for the RC tie case) and the inner tunnel's ring surface.

The present paper intends to outline two SRAs identification methods used in literature and a novel polynomial based method. Their algorithms will be displayed in later chapters, for the present moment the elimination and substitution steps will be dealt with (and their algorithm displayed) with a conforming simplification.

Figure 5. Multiple (a) and all (b) tunnel strain measurements along the monitoring duration (c) with a zoomed section showing the appearance of a HF-SRA (d) compared against the appearance of damage (cracking) in a RC element

SRAs detection in space

SRAs detection in time

Figure 6. Strain anomalies detection versus DOFS coordinates (space) and time

Once the SRAs have been detected the next step is their elimination. Hence, all the detected anomalies are substituted with a *NaN* value (which stands for “Not a Number”) as in the flowchart in Figure 7.

Figure 7. Idea behind the detection of SRAs

NaN (or #N/A) is a numeric data type used by a computing software that represents an undefined or unrepresentative value. As visible later, according to different SRAs detection techniques, specific algorithms are developed for such eliminations. In order to replace the NaN values with correct interpolation substitutes, there are two distinct kinds of interpolation; time and space interpolation which correct their respectively located SRAs. Once again, space interpolation is the only way to delete HF-SRAs. In the strain matrix organization, rows represent the strains along the fiber at particular times, and columns the strain evolution in time of each monitored point. The interpolation algorithm goes through each row or each column looking for the NaN readings and substituting them with an interpolation of the first surrounding reliable strain readings. In order to achieve such when there are multiple NaN readings in a row, the algorithm uses an auxiliary variable k (see algorithm in Figure 8) which starts counting how many anomalies follow it.

When the first non-anomalous reading appears, the counter k stops indicating the index distance at which the algorithm should pick the strain value to interpolate the first one with (the one before the NaN).

Together these two enable the computation of the interpolated values between them (Figure 8). Indeed, the

algorithm is constituted of two parts of which the first actively “looks” for NaN value in the matrix and the second “looks” for the correct values to achieve the interpolation. If the SRA detection algorithm is performant enough, through the correct substitution of all NaN values, a fully improved and SRA free strain matrix is finally achieved.

5 POST-PROCESSING METHODS

With the logical steps of the algorithm in mind the present paper intends to outline two SRAs identification (and consequent cleaning) methods used in literature with different levels of sophistication (thus leading to results of variable quality) and a novel polynomial based method.

5.1 Strain Shift Quality (SSQ) method

Besides strain and temperature readings, the ODiSI-A OBR allows for the computation of the Spectral Shift Quality (SSQ) of each reading. The SSQ is described by the provider²⁶, as a measure of the reliability of the corresponding readings by measuring the level of the correlation between the measurement and baseline reflected spectra as in Equation 1 below.

$$SSQ = \frac{\max(U_j(v) * U_j(v - \Delta v_j))}{\sum U_j(v)^2} \quad (1)$$

where:

$U_j(v)$ is the baseline spectrum for a given segment of data
 $U_j(v - \Delta v_j)$ is the measurement spectrum under a strain or temperature variation

$*$ is the cross-correlation operator

In other words, it is a function that determines the quality/reliability of a strain reading by correlating the original baseline measurement and the measurement spectra normalized by the maximum expected value.

Figure 8. General SRA substitution algorithm

According to its definition, the SSQ value remains between 0 and 1, where 1 translates into a perfect correlation and 0 into an uncorrelated value. The provider states that the data sets are accurate if the SSQ is higher than 0.15 meanwhile, if it is lower, it is very likely that the read strain or temperature has exceeded the measurable range.

In this investigation, the SSQ function is proposed and assessed as a tool for SRAs identification by establishing a minimum SSQ value, or *SSQ threshold*, with which one can invalidate a percentage of SRAs. The minimum/optimal SSQ threshold that allows for the deletion of the highest percentage of SRAs while producing a physically interpretable set of data is a case by case and trial and error matter. Its only constraint is that it has to be above 0.15 (as recommended by the ODiSI software manufacturer). Figure 9 depicts the algorithm required to perform an SSQ data post/processing.

This algorithm requires as input data the strain and SSQ matrices provided directly by the sensing software and an SSQ threshold below which the respective strain readings will be considered as anomalistic and removed. As explained above, the output is a new strain matrix with missing data (NaN) replacing the identified anomalies.

Figure 10 illustrates the strains measured in DOFS section 1.0425m of the laboratory test's member 12x12_D12.01 at different time steps (not seconds) along with each measurement's relative SSQ value.

What is visible is, first of all, that no clear variation of the SSQ value is present in correspondence to the abnormal strain peaks (HL-SRAs). Secondly, that it is not uncommon that the SSQ value instead of decreasing in correspondence

to the SRAs, it actually increases thus misleading the reader into thinking that those are of the same if not higher quality measurements.

Lastly the value of the SSQ seems to oscillate in quality even in intervals where only good strain measurements are being recorded. This complicates the task of setting an SSQ threshold that distinguishes reliable and unreliable readings thus increasing the risk of indiscriminately removing reliable data along with unreliable ones.

Figure 9. SRAs detection and removal with an SSQ tool

Figure 10. DOFS strain measurements compared to their SSQ

This is evident in Figure 11 which illustrates the outcome of an SRA elimination according to different SSQ threshold values (0.15, 0.25, 0.35 and 0.45) for the laboratory members 12x12_D12.01 and 12x12_D12.02. The latter is presented in three points in time or loading level differently colored for clarity purposes.

The gradual decrease of the SRA peaks with the increase of the SSQ threshold is clear but at the same time it is also noticeable how, for higher ones the trend of originally SRA-heavy segments (such as segment 1.087-1.185m for 12x12_D12.01 and 0.89-0.97m for 12x12_D12.02) is distorted due to an excessively undiscerning points deletion. Figure 11e exemplifies the case where the SSQ threshold is so high that almost no point is considered reliable hence they were all removed. In Figure 11a the SSQ method seems more performant than in Figure 11b to d which is in line with what was suggested above concerning the variability of the results from case to case. Additionally, the SSQ threshold that seems to work best for member 12x12_D12.01, SSQ=0.35, is far from acceptable for member 12x12_D12.02 and vice versa. A universally efficient SRA cleaning method should not perform in such aleatory way.

Figure 11. 12x12_D12.01's (a) and 12x12_D12.02's (b) to (e) SSQ processed strain profiles through different SSQ thresholds

In conclusion despite the SSQ is a good tool to clear the largest SRAs and clarifying the profile trend, it is an excessively rough post-processing tool, unable to consistently provide clean and reliable strain profiles whenever medium/high levels of accuracy and precision would be required.

5.2. Geometrical Threshold Method (GTM)

In order to identify the SRAs, their own definition could be directly used. Indeed, being these strain readings sudden and overly large, they imply a great variation between two consecutive readings. On the ground of such, a maximum strain variation (GT threshold) can be defined and used to identify the appearance of an SRA. This method will be henceforth referred to as *Geometrical Threshold Method (GTM)*. This SRAs identification process based on strain 'jumps' can be applied both temporally and spatially but is unable to detect nor correct HF-SRA since, after the first anomalistic reading, another very similar in magnitude follows so whilst the first might be detected as an SRA, all the following ones won't. Thus this method can only be considered as an HL-SRAs detection method. Figure 12 depicts the algorithm required to perform a GTM data post/processing.

The presented algorithm shows the detection process of strain jumps between consecutive readings (in time). As mentioned before, the detection of jumps between nearby readings might also be required, for that, an exchange of all i and j in the routine would be enough. The possible presence of missing readings in the input strain matrix is taken into consideration to allow for the combination of different SRAs removal routines.

Figure 12. SRAs detection algorithm with a GTM tool

The strain increment ($\max\Delta$) that identifies the SRA has to be carefully chosen so as to avoid deleting correct jumps (related to cracks or sudden load increments) and focus only on the anomalistic jumps. Figure 13 below illustrates the outcome of an SRA elimination according to different thresholds (50, 150, 500 and 1000 $\mu\epsilon$). Figure 13b to e should be compared with the original strains plotted in Figure 11b

Once again the removal of the largest SRAs is immediate and the optimal geometrical threshold is for both members 50 $\mu\epsilon$. Once again though, the anomalies that were corrected were strictly HL-SRAs in addition to a certain amount of profile distortion in the SRAs heavy segments.

5.3. Polynomial Interpolation Comparison Method (PICM)

The Polynomial Interpolation Comparison Method is a routine based on the very simple concept of what is an error. The core idea is based on the development of an approximated polynomial curve of the study case DOFS section's ϵ - t profile which encompasses the maximum number of reliable strain readings of the profile (effectively representing its trend). The polynomial degree can vary to provide improved fitting even though, generally talking, it should be neither too low (which would lead to non-representative tendencies), nor too high (because the trend would in return be affected by the punctual anomalies).

As example, Figure 14 below represents different DOFS sections of member 12x12_D12.02 with the original data (thin blue) including clear anomalies, the selected polynomial curve in red and finally the corrected data in green. When the strain matrix includes SRAs of small magnitude it is possible to automatically generate polynomial fitting curve as in Figure 15a for the experimental member 12x12_D12.01 and Figure 15b for the DOFS tunnel deployment (approximation ϵ - t curve in red and pink for two measuring points in critical locations). Instead, when the strain matrix includes SRAs of high magnitude, developing a trend line would be meaningless since the amount of SRAs would affect its profile preventing it from reflecting the real behavior of the section (as in Figure 14a). In this case a manual defining and plotting of the curve is possible. The DOFS strain curve is compared to the polynomial approximation curve resulting in a certain amount of error per measurement.

Figure 13. Member 12x12_D12.01's (a) and 12x12_D12.02's (b) to (e) strain profiles processed with the GTM method and different maximum strain thresholds

Figure 14. Strain measurements along time of anomalous DOFS sections versus their polynomial curve approximations (in red) of member 12x12_D12.02

Figure 15. SRAs detection with PICM of laboratory tests' (a) and tunnel's (b) readings when the SRAs' magnitude is small

Following the definition of a maximal error between the two curves' points, whenever the error is higher than such established limit, the reading is considered as an SRA. This is achieved through a very simple function that checks the difference between the reading and its corresponding expected value (belonging to the ϵ -t curve approximation) as in Equation 2:

$$\begin{aligned} \text{Error}_i &= |\epsilon_{DOFS,i} - \epsilon_{APROX,i}| \\ \text{if } \text{Error}_i > \text{Error}_{max} &\Rightarrow \epsilon_{DOFS,i} = \text{SRA} \\ \text{if } \text{Error}_i \leq \text{Error}_{max} &\Rightarrow \epsilon_{DOFS,i} \neq \text{SRA} \end{aligned} \quad (2)$$

The choice of the threshold value Error_{max} has to be, as always, a result of an in-depth study of the measured tendencies and peaks. Figure 16 depicts the algorithm required to perform a PICM data post/processing. The latter requires as input data the raw strain matrix, its previously developed polynomial fit and a maximum error that is accepted between them (maxError). The difference between the matrices is computed and, when it exceeds the maximum error, the polynomial fit matrix element substitutes the strain matrix one. As mentioned for the GTM routine, the

maximum error has to be carefully defined to avoid the removal of correct strain measurements.

Figure 16. SRAs detection algorithm with a PICM tool

Figure 17. Member 12x12_D12.02's original strain profiles (a) processed with the PICM method (b) and finally the output (c)

Figure 1 displayed in red the outcome of a PICM post-processing of one of the 12x12_D12.01 member's DOFS strain profiles. Expectedly all the peaks were removed providing us with a clear and distinguishable outline. Similarly, Figure 17 displays respectively the raw strain profiles as extracted by the OBR from member 12x12_D12.02 at three points in time or loading level, a representation of the stitching job performed by the post-processing algorithm versus the original data and finally the much improved SRA-free output.

It should be noted though that, as per the other methods, in the presence of too many consecutive SRAs, their removal and interpolation might lead to segments of the graph with a higher degree of uncertainty. This is the case of the profile corresponding to the bare segment of the rebar between the two concrete blocks (0.89-0.97m). The same could be stated for member 12x12_D12.01 for DOFS coordinates 1.095-1.178m. Yet, thanks to this method's ability to recognize reliable values in between SRAs, the overall unreliability of the PICM extracted profile is clearly inferior to the SSQ's and GTM's.

6 POST-PROCESSING RESULTS OF REAL-LIFE STUDY CASE SCENARIO

In the present chapter the above explained post-processing algorithms are used to clear out the SRAs from the strain matrix originated by the in-situ tunnel monitoring along 300 days.

The first adopted method is the SSQ. As can be seen in the Figure 18b to d, different SSQ thresholds provide different outcomes compared to the original strain data represented in Figure 18a.

An obvious aspect of this figure is that the total amount of SRAs decreases as the SSQ threshold increases. Despite still presenting a significant amount of anomalies (in particular HF-SRAs), the best fit (surrounded in red) can be achieved after the removal of the measurements with associated SSQ values lower than 0.30. A lower threshold, presents an

uninterpretable set of data due to an excessive amount of SRAs, whilst a higher one translates into too many measurements being deleted.

Despite the global trend can be distinguished, the graphs are still plagued by enough SRAs to lead to interpretation confusion which is detrimental when monitoring the need for emergency maintenance into the tunnel. Thus, SSQ cannot be considered a reliable post-processing method.

Passing on to GTM, when approaching an SHM monitoring of a real case scenario with this post-processing analysis, a lot of care should be taken when deciding the threshold. Indeed, when the structure's future behavior is completely unknown to the engineer, it may suffer large strains peaks (for example due to the appearance of cracks or impacts) which might but should never be confused with SRAs. This is particularly valid when DOFS are bonded to the structure's external structural surface (as seen in literature^{23,19}) as is the case for the present study scenario. In this case a GTM analysis should be performed in the direction where there are the least expected sudden strain jumps; along space (along the DOFS coordinates). Thus, assuming that in the present case the strains do not vary more than $250\mu\epsilon$ in less than 10mm (not even when cracking is considered) the resulting GTM post-processing is represented in Figure 19a.

Despite the actual size of the SRAs isn't excessive, their disproportionate amount still present in the post-processed surface plot implies the poor performance of GTM as a post-processing tool for an in-situ superficial monitoring. Even when lowering the Geometrical Threshold to $50\mu\epsilon$ (Figure 19b) a large number of anomalies would still be present. Moving on to the PICM analysis, given the original data matrix (plotted in Figure 20a), the best polynomial fit is calculated for the evolution of the strains in each DOFS coordinate along time (as exemplified by Figure 15b) which, combined together, provide the polynomial fit represented in Figure 20b. Despite not being composed of actual measured points, Figure 20b already provides a good feeling of the strain evolution in each segment of the tunnel.

Figure 18. DOFS-extracted strain measurements of segment 10-50m (a) and the result of SSQ post-processing for different SSQ thresholds (b) to (d)

When finally developing a PICM comparative fit between the original data (Figure 20a) and its extracted trend-lines (surface in Figure 20b), the post-processed output of the strain matrix (Figure 20c) is a much improved surface plot compared to its original state. Indeed, having been the largest amount of SRAs successfully eliminated, the layout is immediately clearer and strictly composed by actual DOFS reliable measurements.

7 POST-PROCESSING METHODS COMPARISON

In the previous sections the inner workings of each post-processing algorithm were discussed along with a look at their performance. A final comparison amongst these is presented in the following by putting side to side strictly the

output of the analysis that performed best (in case of SSQ and GTM the thresholds that provided the highest amount of SRAs correction) for each post-processing method. Figure 21 below summarizes the latter by collecting the plots whose parameters provide the best fit to the reliable points of the original DOFS extracted strain profiles for member 12x12_D12.01 and 12x12_D12.02.

For members 12x12_D12.01 and 12x12_D12.02 their respective SSQ thresholds are 0.35 and 0.25 whilst their selected GTs' is $50\mu\epsilon$ for both. Figure 21 shows how for all diagrams removing the HL-SRAs provides a relatively trust-worthy diagram. For member 12x12_D12.01, the only method that not only takes advantage of all the reliable points to plot the graph but also extracts a somewhat symmetrical profile is the PICM method.

Figure 19. GTM post-processed DOFS-extracted strain measurements for a geometrical threshold of $250\mu\epsilon$ (a) and $50\mu\epsilon$ (b)

Figure 20. Original DOFS extracted strain evolution in time (a) which, when combined with a polynomial fit (b), results in P1CM processed output (c)

Figure 21. SRA-cleaning post-processing methods comparisons for member 12x12_D12.01 (a) to (d) and 12x12_D12.02 (e) and (f)

Figure 22. SRA-cleaning post-processing methods comparisons (SSQ (b), GTM (c) and PICM (d)) for the in-situ tunnel monitoring versus the original strains (a)

Oppositely, SSQ and GTM (the former more than the latter) indiscriminately removed the data in the right branch of the graph thus giving it a false inclination that does not envelop nor represent the points there present. The strain profiles of member 12x12_D12.02 are quite rectilinear, thus decisively compatible with a rougher anomalistic detection and removal method such as SSQ and GTM. For this reason, the profile extracted from these methods are quite similar to PICM's in Figure 21f.

Moving on to the tunnel monitoring, once again PICM seems to be the method that provides the best results as can be seen in Figure 22. As a matter of fact, almost all SRAs are removed whilst in the other two cases only partially. As proven by the SSQ and GTM results, HF-SRAs is the kind of anomaly that proves to be the hardest to remove due to its hard detection. Despite such, PICM successfully proceeds to eliminate these too.

In conclusion, considering both the post-processing results extracted from the laboratory RC ties test and the tunnel monitoring, the most consistently reliable method is PICM as it delivered trust-worthy mostly-SRA-free strain profiles for both. This should definitely be the preferable post-processing technique for monitoring cases where precision is a hard requirement such as laboratory work and detailed analysis aimed at taking important intervention decisions (such as the case of the in-situ monitoring). As previously suggested the SSQ and GTM methods are faster and simpler but cruder post-processing approaches adapt only for quick and general checks.

A Strengths Weaknesses Opportunities Threats (SWOT) graph encapsulating all of the previous points is suggested in Table I. It summarizes the advantages and disadvantages of each post-processing method thus helping in the choice of most fitting method for different applications.

Table I. Strengths Weaknesses Opportunities Threats (SWOT) graph

STRENGTHS		WEAKNESSES
SSQ	<ul style="list-style-type: none"> - Low computational cost thus speed - largest SRAs treatment - Roughly clarifies global trend 	<ul style="list-style-type: none"> - No consistent correlation between anomalies and SSQ values - Complicated SSQ threshold setting - High risk of indiscriminately removing reliable data along with SRAs
GTM	<ul style="list-style-type: none"> - Medium computational cost thus speed - Based on anomalies' definition - Able to detect HL SRAs 	<ul style="list-style-type: none"> - Unable to detect HF SRAs - Complicated jump threshold setting - Profile distorts in SRAs heavy segments
PICM	<ul style="list-style-type: none"> - Based on simple error concept - Able to detect both HL & HF SRAs - Provides clear, distinguishable and physically interpretable outline 	<ul style="list-style-type: none"> - High computational cost - Not fully automatized as it requires manual fitting in SRAs heavy segments.
OPPORTUNITIES		THREATS
SSQ	<ul style="list-style-type: none"> - SSQ values are computed by the OBR itself thus providing quick results 	<ul style="list-style-type: none"> - High risk of misinterpretation of the extracted data - Poor efficiency for non-linear loading processes and strain profiles
GTM	<ul style="list-style-type: none"> - Works well with linear/monotonic loading processes and strain profiles 	<ul style="list-style-type: none"> - Misinterpretation of the extracted data - Inadvertent removal of crucial data such as damage peaks - Non-linear loading processes and strain profiles
PICM	<ul style="list-style-type: none"> - Efficiency does not depend on loading processes nor strain profile shape - Works well both for a controlled and monitored environment (lab test) and uncertainly behaving structures (real-life applications). 	<ul style="list-style-type: none"> - High computational and time cost may lead to a delay in the detection of alarming structural deformation/damage

8 CONCLUSIONS

Despite Distributed Optical Fiber Sensors (DOFS) hold huge advantages over classic civil engineering strain monitoring tools, their applicability is limited by sudden disruptive strain reading anomalies (SRAs) that seem to be

inherent to the measuring principle of backscattering taking place in DOFS. These unreliable points usually take the form of large, out of scale strain peaks or isolated drastic upsurge of strain order of magnitude. These anomalies aren't necessarily deal breaking as the DOFS extracted data can be treated with a process of SRA detection, elimination and

finally substitution. The present paper discussed different ways of performing these tasks. The core algorithm of two methods previously used in literature (Spectral Shift Quality and Geometrical Threshold Method) and of a novel polynomial based one (Polynomial Interpolation Comparison Method) was shown and applied to two study case scenarios in order to test their performance. These two scenarios were an experimental laboratory test on two Reinforced Concrete (RC) tensile elements (ties) and an in-situ metro tunnel monitoring campaign. The resulting outputs showed the ability of each of these methods to remove the erroneous and damaging strain readings despite large performance discrepancies. Indeed, despite providing a quick and small computational taxing analysis, the classic methods (SSQ and GTM) were not able to clear out all SRAs in the case of the tunnel monitoring and provided relatively distorted strain profiles in the case of the two RC ties. The novel polynomial based strain interpolation method (PICM), instead, provided output plots free of any strain peak and with the minimum amount of distortion for both. As a result, the latter is identified as the best SRA cleaning post-processing method when accurate and reliable measurement are required.

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Figure 1. DOFS-extracted strains profiles versus DOFS coordinates (a) and versus time (b)

300x300 DPI

Figure 2. Graphical representation of different SRAs' theoretical definitions

300x300 DPI

Figure 3. Study case RC ties (a) with dimensional and DOFS bonding characterization (b)

300x300 DPI

(a)

(b)

(c)

Figure 4. Tunnel DOFS installation (a), picture of the DOFS coordinates ~45.50m (b) and picture of DOFS coordinates from ~20-26m (c)

300x300 DPI

Figure 5. Multiple (a) and all (b) tunnel strain measurements along the monitoring duration (c) with a zoomed section showing the appearance of a HF-SRA (d) compared against the appearance of damage (cracking) in a RC element

300x300 DPI

SRAs detection in space

SRAs detection in time

Figure 6. Strain anomalies detection versus DOFS coordinates (space) and time

Figure 7. Idea behind the detection of SRAs

Vectorial image

Figure 8. General SRA substitution algorithm

Vectorial image

Figure 9. SRAs detection and removal with an SSQ tool

Vectorial image

Figure 10. DOFS strain measurements compared to their SSQ

300x300 DPI

Figure 11. 12x12_D12.01's (a) and 12x12_D12.02's (b) to (e) SSQ processed strain profiles through different SSQ thresholds

300x300 DPI and Vectorial image

Figure 12. SRAs detection algorithm with a GTM tool

Vectorial image

Figure 13. Member 12x12_D12.01's (a) and 12x12_D12.02's (b) to (e) strain profiles processed with the GTM method and different maximum strain thresholds

300x300 DPI and Vectorial image

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Vectorial image

Figure 15. SRAs detection with PICM of laboratory tests' (a) and tunnel's (b) readings when the SRAs' magnitude is small

Vectorial image and 300x300 DPI

Figure 16. SRAs detection algorithm with a PICM tool

Vectorial image

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Vectorial image

Figure 18. DOFS-extracted strain measurements of segment 10-50m (a) and the result of SSQ post-processing for different SSQ thresholds (b) to (d)

300x300 DPI

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300x300 DPI

Figure 20. Original DOFS extracted strain evolution in time (a) which, when combined with a polynomial fit (b), results in PICM processed output (c)

300x300 DPI

Figure 21. SRA-cleaning post-processing methods comparisons for member 12x12_D12.01 (a) to (d) and 12x12_D12.02 (e) and (f)

Vectorial image

Figure 22. SRA-cleaning post-processing methods comparisons (SSQ (b), GTM (c) and PICM (d)) for the in-situ tunnel monitoring versus the original strains (a)

300x300 DPI