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Machine learning for impact detection on composite structures

Stefano Cuomo [a,*], Mario Emanule De Simone [a], Christos Andreades [a], Francesco Ciampa [b], Michele Meo [a]

[a] Department of Mechanical Engineering, University of Bath, Bath BA2 7AY, UK
[b] Department of Mechanical Engineering Sciences, University of Surrey, Guildford GU2 7XH, UK

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ABSTRACT

In order to overcome the current limitations of the impact localisation process in composite materials, such as the a-priori knowledge of the mechanical properties and the direction dependency of the wave speed, a novel method is here proposed based on the machine learning approach. The algorithm is formed by two steps: the first is the training process, in which a baseline consisting of the structural responses due to impact tests is acquired; the second one evaluates the impact location exploiting the highest cross-correlation coefficient, obtained after the interpolation of the impact response baseline using the Radial Basis Function (RBF) method. Numerous experimental tests are performed on a simple carbon fibre reinforced polymer (CFRP) plate fitted with three piezo-sensors at three different drop heights to validate the training process. The results showed high accuracy in both the reconstruction and the impact localisation, with an error less than 10 mm.

Selection and peer-review under responsibility of the scientific committee of the 12th International Conference on Composite Science and Technology.

1. Introduction

Advanced and complex composite structures are nowadays widely used in aerospace field due to the outstanding in-plane mechanical properties and low density of composite materials. Despite these valuable specific properties, composites have low resistance towards external impulsive loads (out-of-plane) [1]. A particular class of out-of-plane loads is Low Velocity Impact (LVI). This event is commonly defined as an impact where the stress wave does not consistently affect the stress distribution in the structure [2]. Consequences of this type of impact are the Barely Visible Impact Damage (BVID), in which not visible by visual inspection failures could grow in the structures, leading to a detriment of mechanical properties with possible catastrophic consequences. In this context, a technique capable to detect and localise impacts would be useful in order to highlight, during manufacturing and maintenance activities, any event that could badly affect the performance of structures during real operating conditions.

Impact identification and localisation methods have been proposed in literature using different approaches. Primary methods were based on the triangulation technique, but these were limited to applications with homogenous materials of known wave speed [3]. In further studies, a modified version of the triangulation technique was introduced to isotropic materials without the need for prior knowledge of the wave speed [4]. Kundu et al. developed a method based on the minimisation of an error function, capable of locating the impact source in isotropic and anisotropic plate. However, this algorithm required the determination of the wave speed in different direction [5]. Ciampa et al. proposed a technique for impact localisation in anisotropic plates of unknown mechanical properties and wave velocity direction dependency. That was achieved with a fixed configuration of six sensors and by solving a set of nonlinear equations aided by local and global optimisation methods [6,7]. In addition, De Simone and Ciampa developed a method capable of detecting the impact location in isotropic and composite samples, using four surface-bonded transducers, with no requirement for pre-calculation of the wave propagation speed in the test sample [8].

Although the aforementioned methods are effective, some of them are dependent on the prior knowledge of parameters such as the material properties and the directional wave speed, whereas others require a fixed configuration of sensors.

In order to overcome these limitations, the aim of this research work is to introduce a Time Reversal (TR) method capable of localising impact events in structures with complex geometries, made

* Corresponding author.
E-mail address: S.Cuomo@bath.ac.uk (S. Cuomo).

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of CFRP (anisotropic) with unknown mechanical properties and without the need for specific sensor configurations.

In previous works [9–11], TR was applied by measuring the structural response of a set of calibration points on the specimen and then cross-correlating these recorded signals with the signal from an actual impact. The cell with the maximum correlation coefficient, obtained by averaging cell corner points, was considered the "impact cell". The actual impact location was then evaluated using a centre-of-gravity method [12].

In this work, TR approach is improved and implemented in order to realise an algorithm capable to detect and locate an impact, suitable for composite panels, but eventually even for structures with complex geometries and different materials. Moreover, to achieve the goal of this study, Machine Learning (ML) is also implemented. ML is a branch of Autonomous Learning that is defined as the process of learning without human intervention [13]. In particular, with ML it is possible to process the acquired data using an algorithm and convert them into parameters which in turn could be used to interpret future data.

The novelty proposed in this work relies on the ML application to train the algorithm to localise low-velocity impacts in structures with different materials and geometries. The training process is executed by using the Radial Basis Function interpolation method, to extrapolate structural response data from the whole structure. Moreover, an improved impact localisation routine is introduced in this work, using the "Centre of Gravity" method to evaluate the impact coordinates.

Three experimental set-ups are considered, each of them at a different drop height, in order to evaluate the robustness of the proposed algorithm.

2. Machine learning for impact localisation

In this section the methodology applied to develop the proposed technique is introduced and explained. The principal aim is to exploit the ML to improve the capability of the TR approach, in order to localise an impact event on composite structures. The localisation process is based on multiple steps that are hereafter listed and developed. The first stage is the calibration process, when the structural responses are acquired at the transducer locations and stored, forming a data baseline for the algorithm. The second step is the learning process (ML), where the data captured in the calibration phase are used to train the algorithm. After the signal acquisition due to a generic impact event, the correlation is evaluated. The training process proceeds with the extrapolation of the correlation parameter between baseline and impact signals on the whole structure in a refined number of points. The impact coordinates are then estimated by the "centre of gravity" method.

2.1. Calibration

The specimen/structure is discretised in multiple square cells, with dimensions dependent on the specimen size and extension of the monitored area. In this research work, cells with dimensions of 40 mm $\times$ 40 mm are considered, seeking a trade-off between resolution of the structure responses and calibration process duration. The response of the structure is acquired at each cell corner by mean of piezo-sensors (each corner is named calibration point). In order to avoid variation and errors, the response at each point is acquired three times, so that a unique response is obtained averaging the acquired signals. The response is then stored in order to realise a data baseline for the localisation algorithm.

2.2. Machine learning

An impact event is executed on the structure, to register the signals acquired from the attached piezo-sensors.

The learning process hence starts from the evaluation of the correlation between impact and baseline signals by means of the TR method.

Time Reversal method is based on time reversing the impact response of the structure and virtually reemitting it from the sensors (as is acting as a transducer) [14]. Then the correlation between the structural responses and the unknown impact is evaluated. This mathematical process can be interpreted as a coherence estimation to identify a relation between the reference signals, the baseline, and the actual impact event. The acoustic source location is then estimated by the maximum correlation value.

To avoid attenuation issues affecting this method when anisotropic materials are considered, a normalisation process involves the time reversal operator, obtained by performing the cross-correlation between the impulse responses from the baseline and the impulse response from the actual impact:

$$R_{\mathrm{TR}} = G(\boldsymbol{r}_m, t; \boldsymbol{r}) \otimes G(\boldsymbol{r}, -t; \boldsymbol{r}_{m0}) = \int_0^t G(\boldsymbol{r}_m, t; \boldsymbol{r}) G(\boldsymbol{r}, t+\tau; \boldsymbol{r}_{m0}) d\tau$$

$G(\boldsymbol{r}_m)$ is the response acquired during the calibration process at the location $\boldsymbol{r}_m$. $G(\boldsymbol{r}_{m0})$ is the response due to the actual impact at the generic unknown impact location $\boldsymbol{r}_{m0}$. τ is the time lag.

Indeed, the time reversal operator is normalised with respect to the energies of the response signal due to the actual impact ($E_{Gr_{m0}(t)}$) and the baseline signals ($E_{Gr_m(t)}$):

$$R_{TR}|_{norm} = \frac{|R_{TR}(t)|}{\sqrt{E_{Gr_m(t)} E_{Gr_{m0}(t)}}}$$

The cross-correlation coefficient, calculated as the maximum value of the normalised time reversal operator (2), spans between:

$$0 \leq C_{TR} = \max\left(R_{TR}|_{norm}\right) \leq 1$$

Values towards one indicate that the signals are correlated, whilst values towards zero are representative of uncorrelated signals [12].

The number of cross-correlation coefficients is related to the baseline cells dimensions. The training process hence pass through the extrapolation of response information in the whole structure in order to create a refined map for the correlation. This is obtained by means of the Radial Basis Function interpolation method (RBF).

The input data (parameters) for the RBF are the N known cross correlation coefficients (cc-coefficients), one for each cell corner, whereas the unknown data are the cross-correlation coefficients at M refined points on the structure surface. Given the input, N cc-coefficients of the baseline, the corresponding output, M refined cc-coefficients, is obtained. By applying the RBF, the learning process is completed, and is possible evaluate the impact location.

2.3. Impact localisation

Once obtained the complete cc-coefficient distribution among the M refined points on the structure, it is possible to detect the impact location. In previous works [15] the localisation process is performed by the identification of the cell with highest averaged cc-coefficient value (obtained by averaging the values related to each cell) and the evaluation of the impact coordinates within the spotted cell by applying a gravity method.

In thin plates or in complex structures, the localisation process based on a cell averaged value from the cross-correlation application could compromise the performances of the algorithm. This happens when two or more baseline cells show similar cc-coefficient averaged values, furnishing a misleading impact location as output. To avoid this inconvenient, an improved impact localisation algorithm is developed, in which the impact location is identified without using averaged cross correlation coefficients. Afterwards, the impact coordinates estimation is evaluated by mean of the centre of gravity method, as follow:

$$x_I = \frac{\sum_{i=1}^{M+N} x_i c_i}{\sum_{i=1}^{M+N} c_i},$$

$$y_I = \frac{\sum_{i=1}^{M+N} y_i c_i}{\sum_{i=1}^{M+N} c_i}$$

where N is the number of baseline points, M represents the arbitrary set of refined points among the sample surface and c_i is the cc-coefficient (actual and interpolated).

2.4. Accuracy

The level of accuracy of the method is evaluated by the error location function Ψ given by the following equation:

$$\Psi = \sqrt{(x_{real} - x_{calculated})^2 + (y_{real} - y_{calculated})^2}$$

3. Experimental setup

In order to validate the proposed method, a set of tests were executed on a CFRP plate with dimensions 300 mm × 300 mm and 2 mm thickness. The plate is fitted with three piezo sensors with a central frequency of 300 kHz. Fig. 1 shows details of the tested specimen.

The impacts were generated by a free drop weight configuration, at different energy levels. The signals were acquired with an eight-channel oscilloscope with 16 bits of resolution and a sampling rate of 2 MHz.

For the calibration process, the plate was discretised in 25 cells, with dimensions 40 mm × 40 mm, obtaining 36 corners representing the calibration points of the baseline. In Fig. 2 the baseline with the calibration points are depicted.

4. Results

A set of impact tests were performed on the considered plate (executed in two different locations) and the Machine Learning method exploiting the Time Reversal technique was used to evaluate the exact location of the impact event.

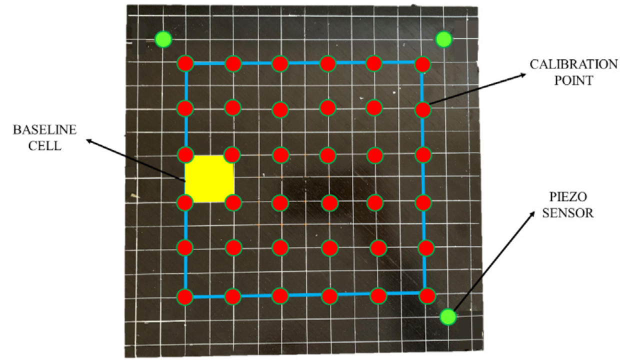


Fig. 2. Baseline cells and calibration points.

To highlight the differences with the old localisation process used in previous works, firstly the localisation results from the old algorithm are shown (see Fig. 3), with a drop height of 100 mm.

As depicted on the previous Fig. 3, the impact estimation error is evident in both cases, with a Ψ value equals to 88.3 mm (left) and 41.5 mm (right).

After the application of the ML method, the algorithm is induced to a training process, at the end of which a set of parameters, representing the RBF reconstruction results, are obtained as outputs. This new set of data is regarded as the input for the localisation process.

As is possible to notice in Fig. 4, after the training process a refined estimation of the cross-correlation distribution over the specimen is obtained. This prediction was possible using the baseline cc-coefficient values as target data. After the training process the impact location (same drop eight) was calculated, with the results reported in the figures below.

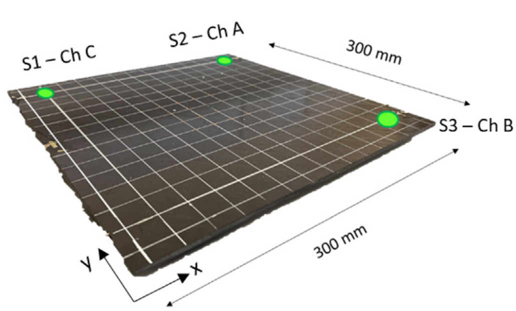
By using the ML and the new improved localisation algorithm, the error for the two configuration is equal to 8.7 mm (left) and 2.8 mm (right), hence the error between the actual impact (green circle in Fig. 5) and the calculated one (black cross in Fig. 5) is significantly decreased.

Furthermore, Fig. 6 reports the impact location results for three different drop heights, equal to 50, 100 and 150 mm, performed at same location.

It is possible to appreciate the good impact location estimation thanks to the new improved impact localisation algorithm.

The error is equivalent to 8.8 mm at 50 mm (top-left), 9.5 mm at 100 mm (top-right) and 9.8 mm at 150 mm (bottom) drop height.

In Table 1 the comparison between the Ψ values related to the new improved localisation method and the old one is reported, showing a better localisation approach.



	x-Coordinate (mm)	y-Coordinate (mm)
SENSOR 1	35	277
SENSOR 2	257	277
SENSOR 3	257	42

Fig. 1. Test specimen and sensors configuration.

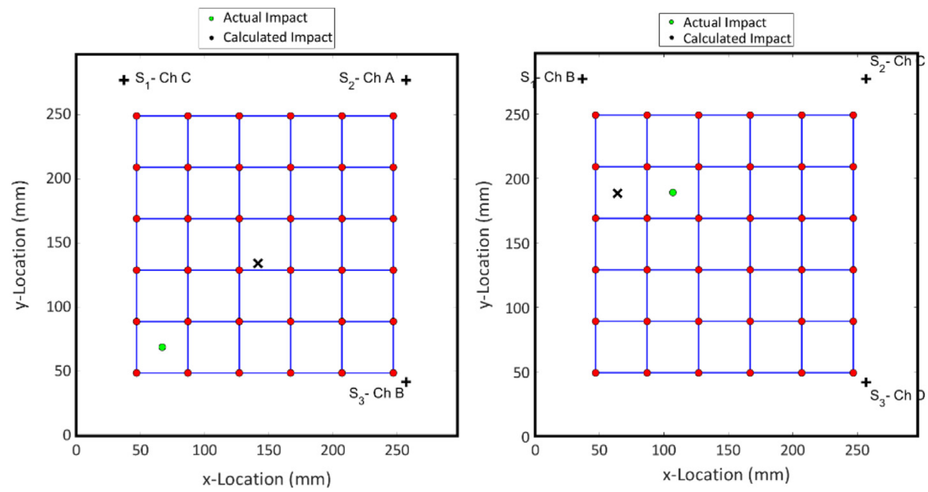


Fig. 3. Impact location - old algorithm.

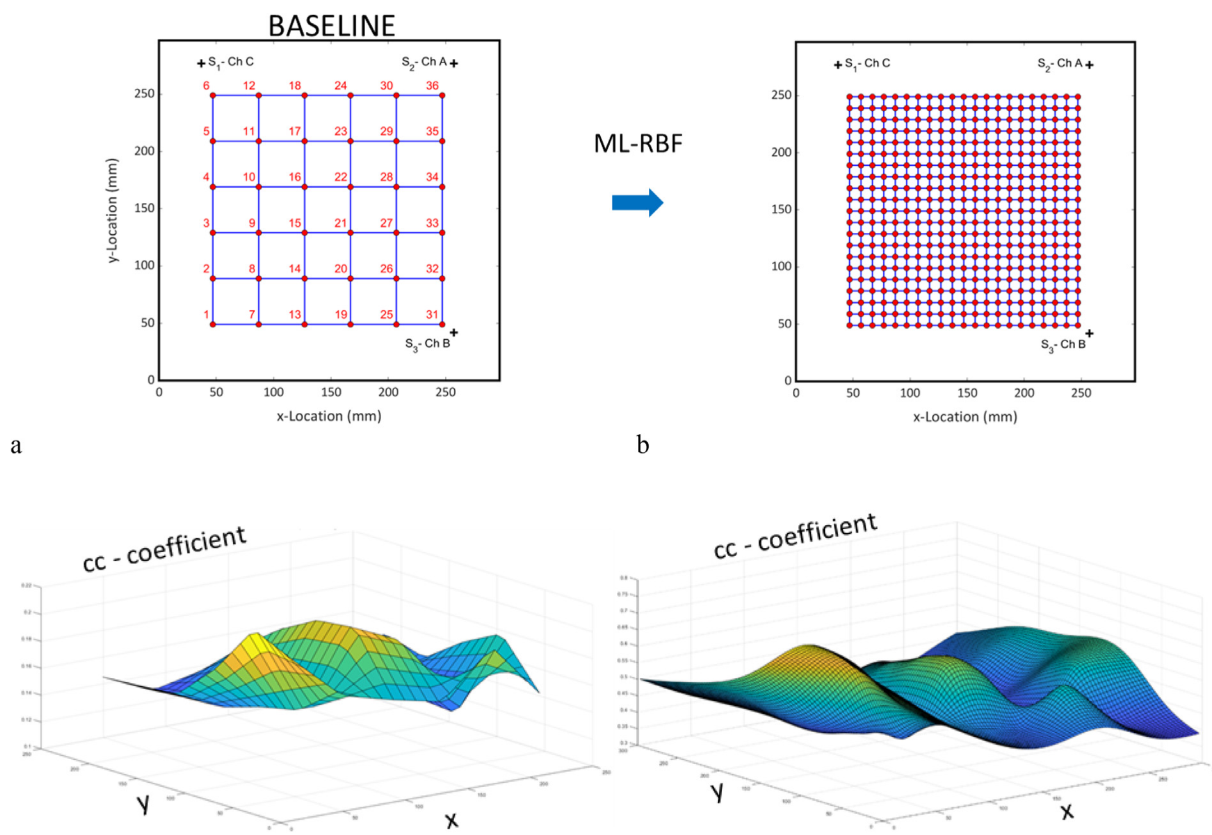


Fig. 4. Learning process and cc-coefficient distribution on the plate: coarse (a), refined (b).

5. Conclusions

A new impact localisation method for composite material structures using Machine Learning algorithms is presented. The proposed method is based on the time reversal technique, able to overcome the limitations of the previous proposed localisation methods, such as the a-priori knowledge of the mechanical properties of the material, the wave speed direction dependency and the use of fixed sensor configurations. The training process is executed via a Radial Basis Function interpolation approach, providing a high level of accuracy which is fundamental for the reconstruction process. The experimental results showed a very good improvement in the impact location estimation, with a reduction of the error function Ψ around 90% in both considered cases. Moreover, accurate results are obtained at different energy levels (50, 100 and 150 mm drop heights), with an estimated location error below 10 mm in all the configurations.

Results show that the application of the Machine Learning is a promising solution for the impact location estimation. Moreover, the new impact location algorithm being not influenced by the location of the impact or by the height of the dropping object, is able to mitigate the instable results showed by the previous method based on the averaged cc-coefficient values.

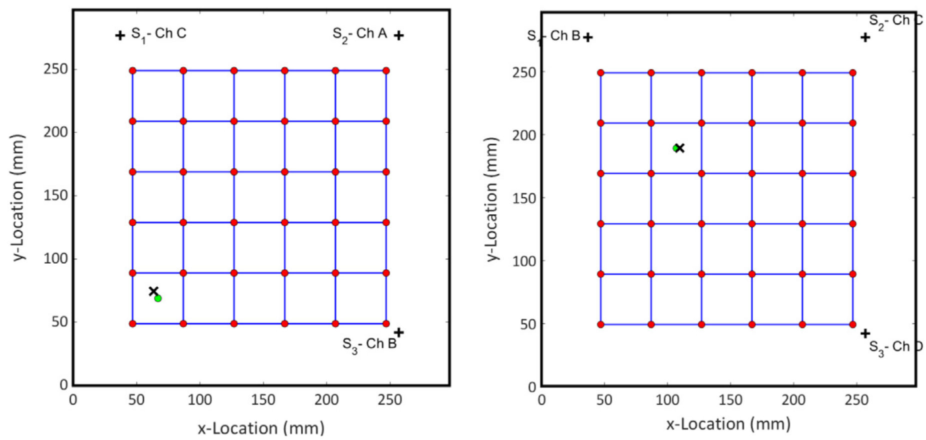


Fig. 5. Impact Location - new algorithm.

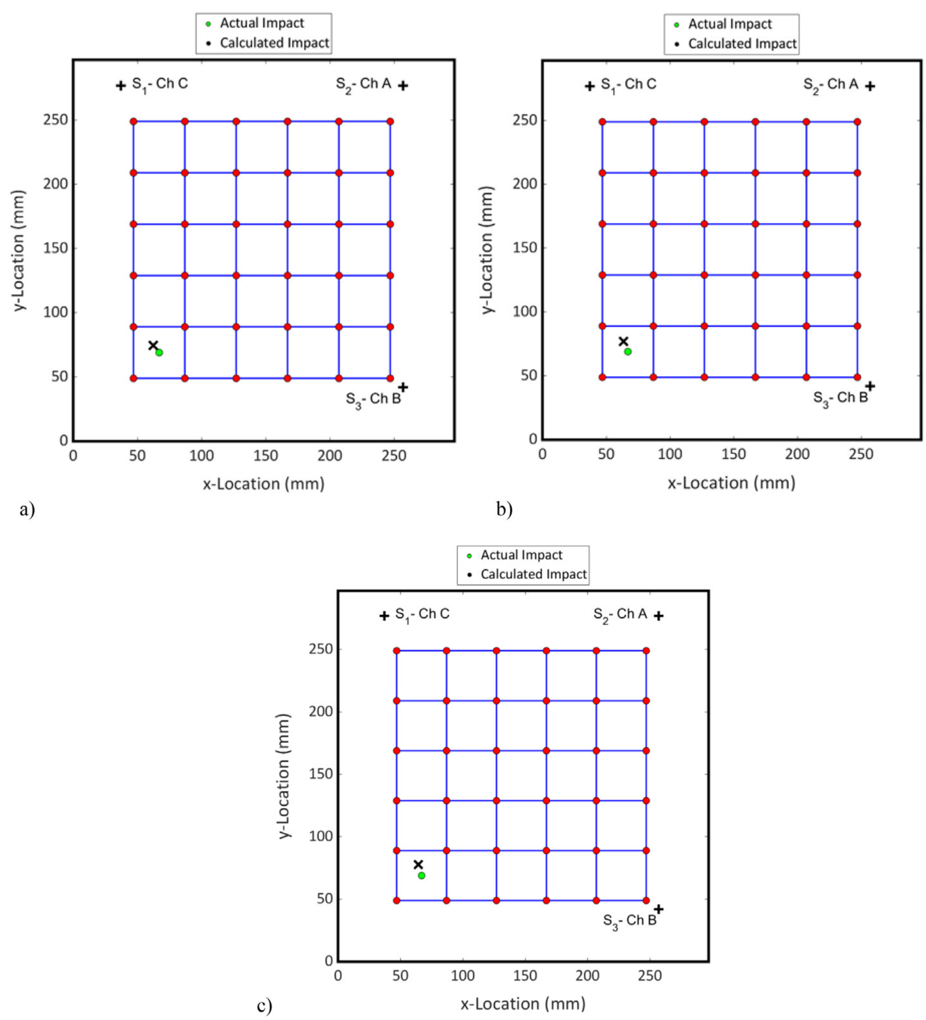


Fig. 6. Impact location: 50 mm (a), 100 mm (b), 150 mm (c).

Table 1
Localisation error comparison.

	Cell 1		Cell 2	
	OLD	ML	OLD	ML
Ψ (mm)	88.3	8.7	41.5	2.8
Δ%	/	−90%	/	−93%

Future works will focus on the possible application of this method on structures with complex geometries (i.e. move from coupon to elements or sub-components) and different materials in order to highlight the effectiveness of the proposed algorithm.

CRediT authorship contribution statement

Stefano Cuomo: Conceptualization, Methodology, Software, Investigation. **Mario Emanule De Simone:** Software, Methodology, Resources, Validation. **Christos Andreades:** Writing - original draft, Resources. **Francesco Ciampa:** Supervision, Writing - review & editing. **Michele Meo:** Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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