Detection of spatial artifacts on resting state functional magnetic resonance data

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Abstract: Brain Functional Magnetic Resonance Image (fMRI) is a widely used non-invasive technique for measuring brain activity and mapping functional regions, but has a complex spatiotemporal structure which complicates the analysis. We present an extension to an existing quality-control (QC) pipeline for resting-state fMRI that automatically detects previously underexplored periodic spatial artefacts. By applying a 3D Fourier transform across each volume and computing inter-slice Pearson correlations over time, we generate summary plots that highlight high-frequency peaks and abnormally elevated correlations, indicative of periodic noise. We integrate these diagnostics in the existing visual and quantitative QC report, allowing reviewers to assign a second periodic-noise PASS/MAYBE/NO-PASS decision based on the presence of periodic noise. In a cohort of 1,178 older adults from the A4 study, our method flagged 42.5% of scans for periodic artifacts that had passed conventional QC. In a classification analysis using a support vector machine with features extracted from the Fourier transform and the spatial correlation analyses against the expert QC labels, we obtained an overall accuracy of 79.5% with a recall for PASS of 92.0%.
Keywords: Resting-state fMRI, Quality control, Periodic spatial artifacts, Fourier transform, Correlation analysis, Support Vector Machine.
SDGs: Health and Well-being, Quality Education, Industry, Innovation and Infrastructure.

I. INTRODUCTION

The human brain operates as a network of distinct regions that are functionally connected and continuously exchange information. Mapping these connections can reveal early indicators of brain diseases such as Alzheimer's disease (AD). Resting-state functional MRI (rs-fMRI) is an effective tool for examining these networks by capturing spontaneous, low-frequency fluctuations in the blood-oxygen-level-dependent (BOLD) signal [1]. When a region of the brain becomes active, the neurons need to consume more oxygen. Therefore, local blood flow increases, leading to a higher ratio of diamagnetic oxygenated hemoglobin (HbO) to paramagnetic deoxygenated hemoglobin (HbR). Because HbR distorts the magnetic field (reducing the MR signal) more than HbO, this hemodynamic response produces measurable changes in signal intensity. These fluctuations, when analysed over time, form a four-dimensional time series that reflects ongoing neuronal activity and allow researchers to track changes in brain function.

After acquisition, raw fMRI data is processed through a sequence of steps to improve quality and reduce noise. For this project, we apply a pipeline developed at the Biomedical Imaging Group (BIG) that performs brain extraction, anatomical segmentation, slice-timing correction, motion correction, spatial smoothing, spatial registration, temporal filtering, and nuisance regression to produce a cleaner signal to explore neural activity [2].

As rs-fMRI studies expand to large and multi-centric, the likelihood of artifacts increases due to high variability in the experiment performance. Thorough preprocessing is essential to isolate the data with genuine neural signals. Quality control (QC) procedures help identify and exclude problematic datasets and preprocessing errors [3]. While the existing BIG QC workflow flags certain registration and motion artifacts, it does not detect other spatial anomalies introduced during scanning or preprocessing. We describe a previously underexplored periodic spatial artifact and propose a simple detection method that combines a 3D spatial Fourier transform (FT) with spatial correlation analysis, integrating these checks into the QC report. Implementing this additional QC measure enhances data reliability and supports more robust conclusions in large-scale rs-fMRI studies.

II. METHODS

The current project is built on an existing semiautomatic QC pipeline that combines visual and quantitative measures and generates individual reports on different preprocessing stages such as brain extraction, anatomical segmentation, slice-timing correction, motion correction, spatial smoothing, spatial registration, and temporal filtering. Using an interactive interface, the reviewer decides whether the subject is considered PASS, MAYBE, or NO PASS for the study. Commonly, this QC are semiautomatic, for instance, if some parameters are above an stablished threshold, a warning is sent to the reviewer to help with the decision.

This QC is a great tool for detecting some registration, motion, and mask-related artifacts specifically. However, it fails to detect other types of artifacts. For instance, some images in the PASS decision of the QC presented a characteristic periodic noise throughout the entire volumes of the same subject (FIG. 1). This is considered a non-physiological noise and directly affects the final analysis. We present an extension of the existing QC by computing 3D-Fourier Transform (FT) and correlation matrix between slices. All procedures have been implemented in Python using packages as numpy and scipy. The results are shown in summary figures added to the QC report, where the presence of peaks in the FT projections and/or the existence of correlated patterns within the image can be easily identified in a quick visual inspection.

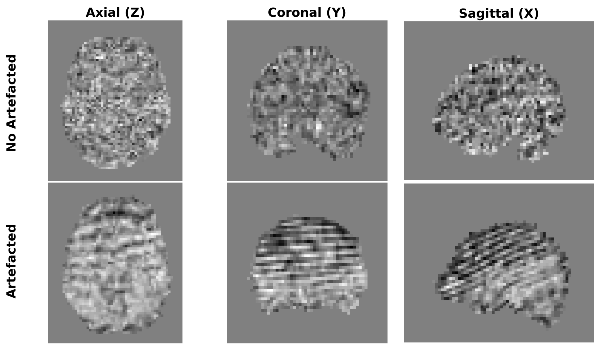

FIG. 1: Examples of rs-fMRI images with and without periodic noise artifacts, shown across three anatomical planes: axial (Z), coronal (Y), and sagittal (X). The top row displays clean (Non-Artefacted) images, while the bottom row shows artefacted images with visible periodic striped patterns.

A. Data

We analyzed rs-fMRI data of 1,178 participants from the A4 study [4] (ages 65-85 years) with normal cognition or very mild cognitive impairment. These had been preprocessed in an automated fMRI pipeline combining in-house developed Python scripts and tools from available packages as FSL (https://fsl.fmrib.ox.ac.uk/fsl/), AFNI (https://afni.nimh.nih.gov/) and ANTs (https://stnava.github.io/ANTs/).

B. Fourier Transform Analysis

The Fourier transform (FT) is a mathematical operator that transforms a function from its original domain (often time or space) into the frequency domain. It essentially decomposes a signal into a sum of periodic functions of different frequencies and amplitudes. This concept can be extended to images in which the information contained in the frequency domain represents different characteristics in the original image.

For instance, low frequencies (located at the centre of the Fourier Spectrum) represent gradual changes in pixel intensity across the image. Therefore, the information of the general shape or overall structure of the image will be contained in this region. High frequencies represent rapid changes in intensity i.e., fine details and abrupt transitions. Thus, the periodic noise that appears in the fMRI images we are working on can be detected as high-frequency components in the Fourier space.

fMRI data are four-dimensional signals (three spatial dimensions plus time). For each individual, we apply the Fourier transform to the entire 3D volume over time, rather than slice-by-slice, which saves computation and gives a global insight into the presence of spatial artifacts in the whole volume. Then, to see how the frequencies spread through 3D space, we sum the spectral values along each axis to highlight the main frequency components and represent them in simplified frequency-signal plots. Therefore, we end up with three different plots, each one for every projection, in which we can identify a central peak corresponding to the position in the 3D space of the central frequency, but in some cases there is the presence of secondary peaks pointing to the presence of periodic noise (see examples in FIG 2).

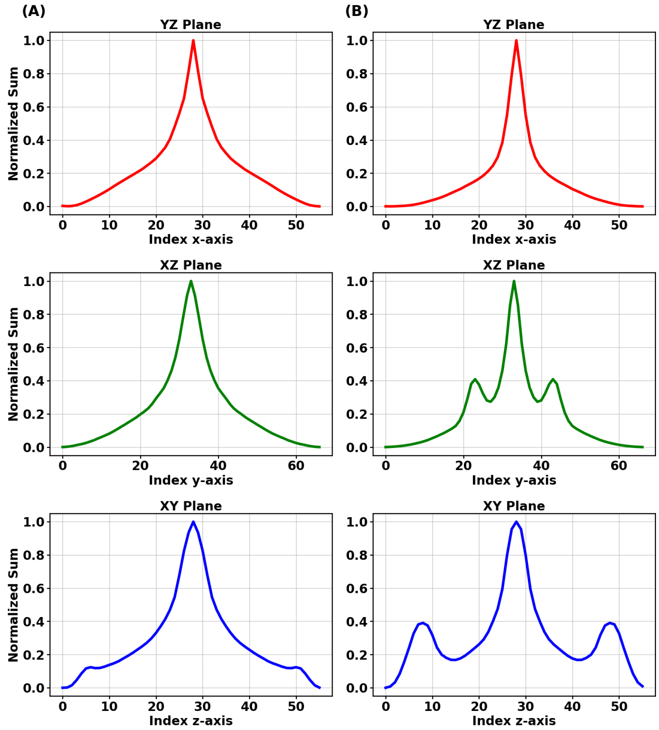

FIG. 2: Mean Fourier Transform (FT) across time points projections along three orthogonal planes. **(A)** Example from a subject classified as PASS, showing no distinct secondary peaks in any projection, indicating the absence of periodic noise. **(B)** Example from a NO PASS subject, where prominent secondary peaks are visible in the XZ and XY projections (y- and z-axis), suggesting the presence of periodic noise.

C. Correlation Matrix Analysis

Correlation matrix analysis assesses how similar signals are across space in time. In fMRI, one typically computes the Pearson correlation between every pair of regions or voxels, producing a matrix that highlights synchronous fluctuations. While correlation matrices are often used for connectivity analysis, they can also highlight artifacts. The idea is that an artefact affecting multiple areas within the same volume will induce an unusual correlation pattern. For instance, if a global physiological oscillation or scanner glitch affects all voxels simultaneously, the correlation matrix would show uniformly elevated values [5]. In rs-fMRI, genuine neural activity should not be correlated across slices, so inter-slice correlation coefficients are expected to be low. However, when a periodic-pattern artifact appears, the resulting matrix often shows elevated correlation compared to artefact-free volumes (FIG. 3).

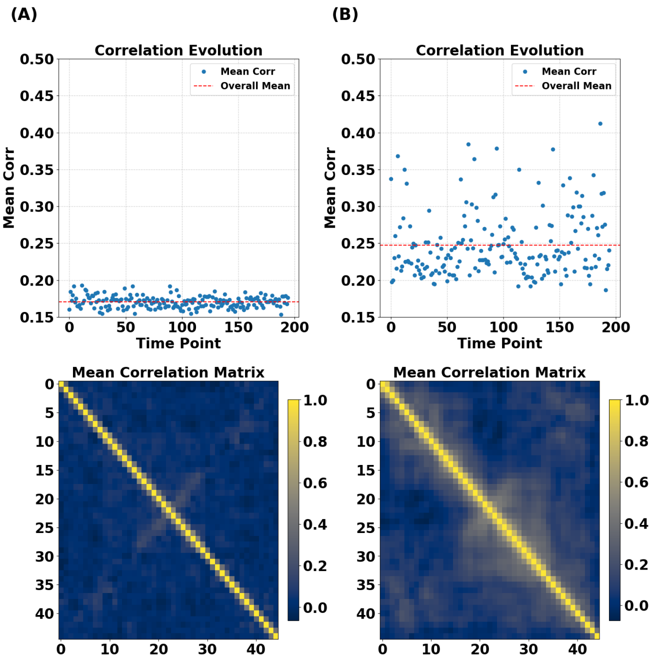

FIG. 3: Temporal evolution and average of correlation values across all files for each time point, along with the mean correlation matrix computed across time. **(A)** Example from a PASS subject, showing consistently low correlation values and low dispersion over time, indicating the absence of artifacts. The mean correlation matrix exhibits no abnormal patterns. **(B)** Example from a NO PASS subject, characterized by elevated correlation values and higher variability, as well as atypical structures in the mean correlation matrix, suggesting the presence of artifacts.

D. Quality Control (QC)

Once the Fourier transform and the correlation analysis have been performed, their results are added to the QC report available for each subject. These report includes interactive buttons where the reviewer can make individual decisions. Two decision can be taken, the already implementented registration errors and the new periodic error decision (FIG. 4).

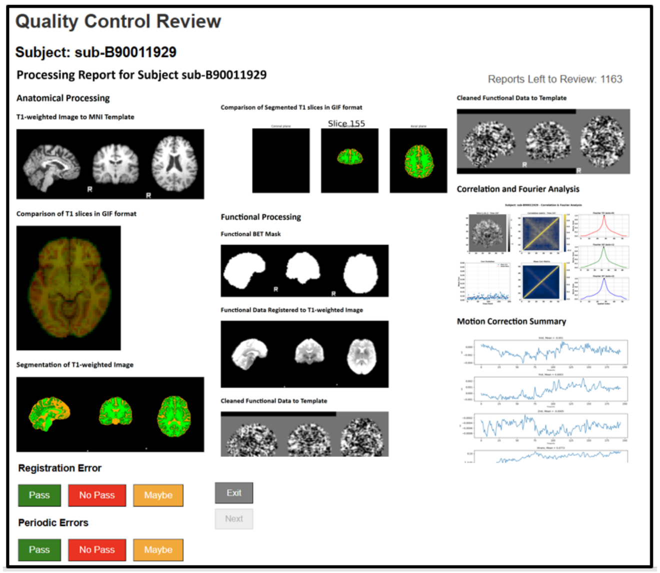

FIG. 4: Screenshots of the QC application in a web browser, displaying visual checkpoints for anatomical and functional processing. The interface also features correlation and FT analyses, along with interactive controls for reviewer input.

E. Independent Component Analysis (ICA)

Independent Component Analysis (ICA) is one of the most widely used techniques for brain fMRI [6]. ICA is a data-driven approach that decomposes multivariate signals into additive subcomponents. It identifies independent components (ICs) from the observed brain signal, producing a set of 3D spatial maps, or components, which are theoretically spatially independent of one another.

ICA generates two outputs: a spatial map showing the brain regions linked to the signal and a time series that describes the signal's evolution over time. The ICA analysis is done using FSL's MELODIC, using the preprocessed fMRI data as inputs. We performed ICA on two sets of images (PASS and NO PASS) to evaluate the effect of the periodic artifact on the resulting spatial maps.

F. Automatic classification

Some features in the images, like the presence of secondary peaks in the FT and elevated values in the correlation analysis, may indicate that an automated model could exist for classifying the images. To do so, we used a multiclass Support Vector Machine (SVM) to sort subjects into three categories (PASS, MAYBE and NO PASS) based on the extracted features. Those where: the total number of points affected by periodic noise, the ratio between the central peak and the secondary peaks in the Fourier space, and for each of the three axes (X, Y and Z), both the mean and the standard deviation of slice-slice correlation.

The model was trained to find the key hyperparameters such as regularization constant C, kernel and kernel bandwidth γ via a grid search within each training fold. Given the size of our dataset, we applied a five-fold cross-validation to ensure robust performance while using all the available data for both training and testing. Finally, we summarise all the predictions into a single confusion matrix, which shows how many subjects for each true class are assigned to each predicted class. From here, we can extract the accuracy of the model as well as the recall for each class.

III. RESULTS AND DISCUSSION

A. QC results

Applying our new QC pipeline that includes the FT and correlation matrix analysis to the 1,178 rs-fMRI scans from the A4 study, we have been able to reveal that a substantial number of subjects in the dataset were contaminated by periodic noise. As summarized in TABLE I, only 613 images were considered as PASS in both decisions (periodic and registration), representing a 52.0% of the original dataset. Therefore, 565 scans that originally passed the registration check were flagged by the newly analysis: 302 as MAYBE and 149 as NO PASS. So, about 42.5% of the scans which would have passed under registration only QC are now eliminated from the final analysis because of the new QC.

Registration \ Periodic	PASS	MAYBE	NO PASS
PASS	613	302	149
MAYBE	4	16	9
NO PASS	30	16	27

TABLE I: QC decision matrix showing the overlap between registration and periodic noise classifications for the A4 rs-fMRI dataset.

B. Effects on ICA components

To examine how these periodic artifacts affect the final analysis, we performed ICA separately on two subsets of data, a PASS set of 200 randomly selected scans from the 613 that passed both QC checks and a NO PASS set of 149 scans that failed the periodic QC. The results (FIG. 5) show a much clearer model in the case of the PASS dataset, having a clearer border from the active region compared with the background. Particularly, in the Coronal (Y) and Sagittal (X) regions, the periodic noise is much higher. This is in concordance with what the FT-space showed us in FIG. 2, in which we can see that extra peaks in the Fourier space can only be seen in the coronal and sagittal directions. Therefore, including artifacted data in the final dataset may contribute to the addition of non physiological signals that can directly affect the study.

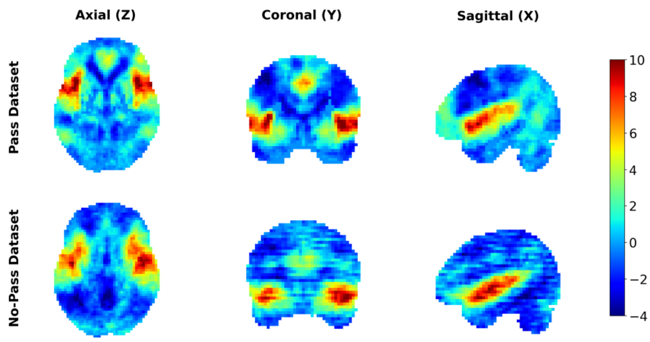

FIG. 5: An ICA component results for the PASS and NO PASS datasets shown across the three orthogonal planes (Axial, Coronal, and Sagittal). Periodic noise is visibly more prominent in the NO PASS dataset, particularly in the coronal and sagittal axis. The colorbar represents z-scores of the ICA component weights.

C. Automatic classification results

Taking into account that quantitative metrics from the Fourier and correlation analysis can effectively distinguish between clean and artifacted scans, we trained a multiclass SVM model to predict QC labels (PASS, MAYBE, NO PASS). The featured data that has been used as an input have been the total number of time points affected detected by the FT analysis, the ratio between the primary FT peak amplitude to the secondary peak, and the mean and standard deviation of the interslice Pearson correlation values along each anatomical axis (X, Y and Z). All the 1,178 subjects from the dataset have been previously labelled manually using the QC. We optimized the hyperparameters of the model and found that the one that allows for better classification is built up with a regularization constant C equal to 1, kernel type RBF and Gaussian-kernel bandwidth, γ scales.

The resulting confusion matrix (FIG. 6) reveals that the SVM correctly identified 592 out of 645 true PASS scans (recall = 92.0%), mislabeling 51 as MAYBE and only 2 as NO PASS. Overall, the classifier achieved 79.5% accuracy. Although the high recall for the PASS class is promising, the performance for the MAYBE and NO PASS categories indicates that improvements must be made. This suggests that additional or more discriminative features may be necessary to distinguish between those scans. However, this has been useful to show the potential of automating QC assessments in large scale rs-fMRI datasets.

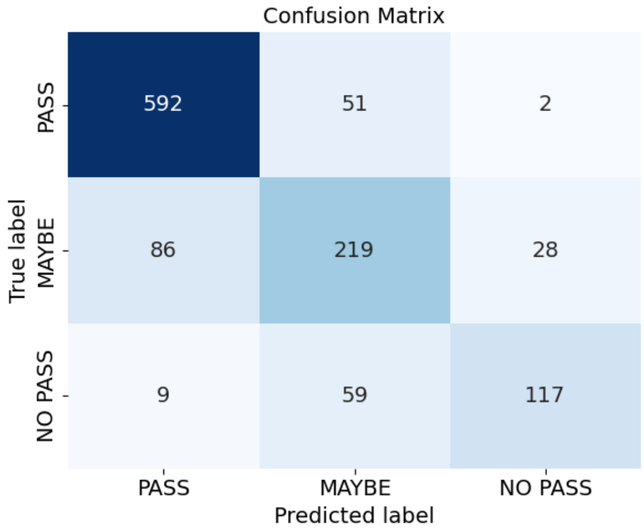

FIG. 6: Final confusion matrix of the SVM classifier for PASS, MAYBE, and NO PASS labels. The model achieved 79.5% overall accuracy, with a recall of 92.0% for the PASS class. Results are aggregated over all test folds from 5-fold cross-validation.

IV. CONCLUSION

In this work, we have introduced an extension to the existing quality-control (QC) pipeline for resting-state fMRI data that automatically detects previously unreported periodic spatial artifacts. By applying a 3D Fourier transform across each volume and performing inter-slice Pearson correlation analysis, we generate concise visual and quantitative metrics that highlight anomalous high-frequency peaks and elevated correlation patterns indicative of periodic noise.

Integrating these diagnostics into the QC report allowed us to review 1,178 scans from the A4 study and reveal that 42.5% of scans previously passing standard QC exhibited periodic artifacts. Excluding these noisy volumes yielded cleaner independent component analysis (ICA) results, with more sharply defined functional boundaries and reduced nonphysiological signals. This amount of misclassification may suggest the need to apply correction methods or identify the source of the artefact, as more than half of the original data is considered unavailable for further analysis.

We also demonstrated the feasibility of automated classification using a multiclass support vector machine (SVM) trained on features derived from Fourier and correlation analyzes. The SVM achieved an overall accuracy of 79.5% and a recall of 92.0% for the PASS category, underscoring the potential of automated periodic noise detection to help reviewers.

Remarkably, this work has been accepted for presentation at an international conference and will be integrated with other group results to be considered for publication.

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Detecció d'artefactes espaials en ressonància magnètica funcional en estat de repòs

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Resum: Imatge de ressonància magnètica funcional cerebral (fMRI) és una tècnica àmpliament utilitzada per mesurar de manera no invasiva l'activitat cerebral i mapar regions funcionals, però té una complexa estructura espaitemporal que en complica l'anàlisi. Presentem una extensió d'un pipeline de control de qualitat (QC) existent per a fMRI en estat de repòs que detecta automàticament artefactes espacials periòdics. Aplicant una transformada de Fourier en 3D sobre cada volum i calculant correlacions de Pearson entre talls al llarg del temps, generem gràfics de resum que destaquen pics d'alta freqüència i correlacions anormalment elevades indicant la presència de soroll periòdic. Aquests diagnòstics s'integren en l'informe de QC visual i quantitatiu existent, permetent als revisors assignar una segona decisió PASS/MAYBE/NO-PASS basada en la presència de soroll periòdic. En una base de dades de 1,178 adults de l'estudi A4, el nostre mètode ha assenyalat el 42.5% dels subjectes com a afectats per artefactes periòdics que havien superat el QC convencional. En una anàlisi de classificació automàtoca utilitzant una màquina de vectors de suport amb característiques extretes de les anàlisis de Fourier i de correlació espacial, enfront de les etiquetes de QC dels experts, vam obtenir una precisió global del 79.5% amb una recuperació del 92.0% per a la classe PASS.
Keywords: Ressonància magnètica funcional en estat de repòs, Control de qualitat, Artefactes espacials periòdics, Transformada de Fourier, Anàlisi de correlació, Màquina de vectors de suport.

ODSs: Salut i benestar, Educació de qualitat, Indústria, innovació, infraestructures.

Objectius de Desenvolupament Sostenible (ODSs o SDGs)

1. Fi de la es desigualtats		10. Reducció de les desigualtats	
2. Fam zero		11. Ciutats i comunitats sostenibles	
3. Salut i benestar	X	12. Consum i producció responsables	
4. Educació de qualitat	X	13. Acció climàtica	
5. Igualtat de gènere		14. Vida submarina	
6. Aigua neta i sanejament		15. Vida terrestre	
7. Energia neta i sostenible		16. Pau, justícia i institucions sòlides	
8. Treball digne i creixement econòmic		17. Aliança pels objectius	
9. Indústria, innovació, infraestructures	X		

El contingut d'aquest TFG, part d'un grau universitari de Física, es relaciona amb l'ODS 3, i en particular amb la fita 3.4, ja que promou l'estudi de malalties no transmissibles com l'Alzheimer. També es pot relacionar amb l'ODS 4, fita 4.4, perquè contribueix a l'educació a nivell universitari, i amb l'ODS 9, fita 9.5, perquè ajuda a promoure la investigació científica i la millora de tecnologies.