Cet outil permet la détection des signatures atypiques, y compris celles ayant des intensités faibles. Cependant les signatures inusuelles ayant des intensités vibratoires équivalentes au bruit sont difficilement détectables car difficilement observables. De plus, les signatures normales liées au N_1 restent détectées à tort. Les différentes approches sont sensibles aux intensités vibratoires et à la position des signatures. Pour le moment, nous détectons uniquement la présence des signatures atypiques sur les patchs, nous ne les classifions pas selon les différents types.

Perspectives

Les principales fausses détections dans les méthodes développées concernent les signatures liées au N_1 qui sont décalées sur les différent spectrogrammes. Du fait de ce décalage, les dictionnaires et les approches ponctuelles caractérisent mal ce type de signature, ce qui entraine sa détection.

Une première approche permettant de palier le problème lié au décalage des raies N_1 est d'effectuer un prétraitement sur les données à travers un clustering du comportement de la relation entre le N_1 et le N_2 sur le spectrogramme. Ainsi chaque spectrogrammes au sein des clusters possèderait des relations N_1/N_2 proches et donc des raies N_1 proches. Les méthodes mises en place seraient alors appliquées dans chaque cluster séparément limitant ainsi les fausses détections liées au N_1. Cette approche nécessite cependant une base de données plus conséquente que la notre afin d'établir un clustering pertinent des spectrogrammes.

Une seconde approche serait d'effectuer la même étude sur des spectrogrammes échantillonnés en N_1 (au lieu du N_2). Sur ces spectrogrammes les signatures liées au N_1 ne se décalent plus et ne sont donc pas détectés. Les signatures N_2 ont de fortes chances d'être détectées à tort dus à leurs décalages. En fusionnant les deux types d'approches en associant les points détectés du spectrogramme en N_2 avec les points détectés du spectrogramme en N_1, il est possible de définir un point atypique comme un point détecté sur les deux types de spectrogrammes.

Tout au long de cette thèse, nous avons étudié les spectrogrammes par patch en comparant exactement les mêmes patchs sur les différents spectrogrammes afin d'en respecter la physique. Il est possible d'augmenter les données en considérant les patchs comme des données indépendantes avec un recouvrement de 50% des patchs dans la subdivision. Les labels "normal" et "atypique" sont alors récupérés pour chaque patch à partir de l'extraction des zones atypiques de la base de données. En considérant l'ensemble de ces patchs comme indépendants, nous nous retrouvons avec une grande volumétrie de données pouvant être considérées comme des images de taille 128×128 avec des labels. A but exploratoire, nous avons testé un réseau de neurones 5 couches [66] pour classifier les patchs et nous avons comparé les taux d'erreurs de classification à un SVM appliqué aux indicateurs images HoG (Histograms of Gradients) [36], SIFT (Scale-Invariant Feature Transform) [76] et LBP (Local Binary Patterns) [86] produisant des descripteurs en grande dimension des points de l'image en fonction de leur voisinage. Sur une base de données de tests, nous avons obtenu un taux de mauvaise classification d'environ 20% pour les réseaux de neurones et de 25% pour le SVM. Nous n'avons pas poussé les études plus loin. Il est encore possible d'améliorer les résultats à travers des modifications des paramètres du réseau ou des structures de réseau plus complexes. Les principaux défauts de ce type d'approche sont la non-prise en compte de la physique en considérant les patchs d'un même spectrogramme comme des images indépendantes, ainsi que leur aspect "boite noire".

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