A FUSION BASED SYSTEM FOR PHYSIOLOGICAL SENSOR SIGNAL CLASSIFICATION

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1. Introduction

Today, usage of physiological sensor signals is essential in medical applications for diagnoses and classification of diseases. Clinicians often rely on information collected from several physiological sensor signals to diagnose a patient. However, sensor signals are mostly non-stationary and noisy, and single sensor signal could easily be contaminated by uncertain noises and interferences that could cause miscalculation of measurements and reduce clinical usefulness. Therefore, an apparent choice is to use multiple sensor signals that could provide more robust and reliable decision. Therefore, a physiological signal classification approach is presented based on sensor signal fusion and case-based reasoning. To classify Stressed and Relaxed individuals from physiological signals, data level and decision level fusion are performed and case-based reasoning is applied as classification algorithm. Five physiological sensor signals i.e., Heart Rate (HR), Finger Temperature (FT), Respiration Rate (RR), Carbon dioxide (CO2) and Oxygen Saturation (SpO2) are collected during the data collection phase. Here, data level fusion is performed using Multivariate Multiscale Entropy (MMSE) and extracted features are then used to build a case-library. Decision level fusion is performed on the features extracted using traditional time and frequency domain analysis. Case-Based Reasoning (CBR) is applied for the classification of the signals. The experimental result shows that the proposed system could classify Stressed or Relaxed individual 87.5% accurately compare to an expert in the domain. So, it shows promising result in the psychophysiological domain and could be possible to adapt this approach to other relevant healthcare systems.

2. Method

Signal classification approach has been done in two ways: 1) sensor signals classification using decision-level fusion and 2) sensor signals classification using data-level fusion. In the decision-level fusion, features are extracted from each sensor signal separately through the traditional feature extraction approaches i.e., considering time and frequency domains features. Five individual case-libraries have been constructed using extracted features from five signals. In the case retrieval step, it retrieves the most similar case from each case-library by matching each individual signal. Thus, the approach retrieves five classes for five signals and a weighted similarity function provides the final classification. In the data-level fusion, the signals are combined by means of a Multivariate Multiscale Entropy (MMSE) [3] algorithm where the algorithm provides us with a number of features. The features that are extracted then construct a new problem case and this new case is then feed into the CBR cycle. Here, the retrieval step retrieves the top most case and classifies the five-combined signal into Stressed or Relaxed class. A CBR [1,2][4,5] approach can work in a way close to human reasoning e.g. solves a new problem applying previous experiences, which is more common for doctors, clinicians or engineers.

3. Results

In CBR, fuzzy similarity function is used for case matching, Leave-one-out approach i.e., one case is taken out at a time to match against the remaining cases in the case library and kNN (K=2) is applied to retrieve similar cases. For the evaluation, two top most similar retrieved cases are considered; if both the query and one of the two retrieved cases belonging to a similar class then the number of correctly classified cases is counted as 1. Here, it is indispensable to mention that each case have been classified by an expert as Stressed or Relaxed. The achieved classification accuracy based on decision fusion is 100% for the Relaxed cases and 75% for the Stressed cases. For both Stressed and Relaxed cases, achieved accuracy is 87.5%. On the other hand, in the data level fusion based achieved classification accuracy is 100% for the Relaxed cases and 75% for the Stressed cases. In total, the achieved accuracy is 87.5%. Accuracy Considering Sensitivity i.e., percentage of cases that are identified as Stressed is 75% and specificity i.e., percentage of cases that are identified as Relaxed, is 100%. So, the overall obtained accuracy is 87% in both the cases i.e., data-level and decision-level fusion based classification.

4. Discussion

In the proposed system, we have applied CBR since in CBR knowledge elicitation can be performed based on previous cases in a case library specially suitable for domains where domain knowledge is not clear such as in classification of sensor signals. We have in the proposed system applied MMSE for the data-level fusion and weighted average algorithm for the decision-level fusion. However, the data-level fusion based on features extracted through MMSE algorithm is more autonomous than the decision-level fusion based on features extracted using traditional approaches. So, such decision-level fusion is encouraged to use while necessary expert knowledge is available. An evaluation of the CBR system based on individual sensor signal has also been performed in this study. It can be seen that the classification accuracy using HR, RR, FT, CO2 and SPO2 are 75%, 87.5%, 75%, 81.25% and 75% respectively. These results imply that all individual parameters except the RR parameter provide less accuracy than both using the decision-level and data-level fusion. Moreover, sensor fusion provides us more reliable and information-rich judgment. Thus, the proposed fusion based approach could be of value to the systems where signals are coming from multiple sources.

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