

# Poster Abstract: SenseEMS - Towards A Hand Activity Recognition and Monitoring System for Emergency Medical Services

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## ABSTRACT

Emergency Medical Services (EMS) providers use their hands extensively for the rescue operation and providing care to the patients in an EMS scene. Using smartwatch based sensor data, i.e., accelerometer, gyroscope, and magnetometer, we are developing SenseEMS, a system for hand operated EMS intervention detection and real-time monitoring. SenseEMS will use a hybrid deep neural network with appropriate real-time algorithms on the sensor data to detect multiple hand operated activities, i.e. CPR compressions, attaching defibrillation pads and breathing bags, and to provide quality assessment on different metrics of the activity, i.e., the rate and depth of CPR compressions. Our initial results for this ongoing research show promising accuracy. Preliminary survey with 31 anonymous EMS responders suggests that this automated system will be highly beneficial for real-scene application and EMS training.

## KEYWORDS

Emergency Medical Services, Sensor Networks, Hand Activity Detection

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## 1 INTRODUCTION

Emergency Medical Services (EMS) providers use their hands extensively to provide various interventions during an EMS rescue. Hand operated interventions include attaching different equipment on the patient's body, administering medications, and performing life-saving procedures such as CPR compressions. Most of these hand operated interventions contain dynamic parameters from both the provider's and patient's point of view. For example, CPR compressions and its metrics vary according to the age of the patient. An EMS provider has to go through different levels of training before performing these interventions in a real scene. Case studies

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in the U.S. show that the EMS programs rarely use any assistive technology for quality assessment. Even today the training for hand operated interventions are guided manually [1]. To improve the quality of interventions and to classify sensitive hand operated emergency interventions, real-time and automated technologies can be adopted for EMS training sessions and actual scenes. [3]. To this end, we propose **SenseEMS**, an automated assistant which will use smartwatch based sensor data for detecting and monitoring hand operated EMS activities such as CPR compressions, attaching defibrillation pads and breathing bags, etc. This is a challenging problem because different responders move their hands differently, there are many confounding hand moving gestures, and even the activities of interest have many similar motions to each other.

Due to the popularity of smartwatches, almost every first responder is willing to wear a smartwatch on their wrist during EMS training and real scenes. This enables us to easily collect accelerometer, gyroscope, and magnetometer data when they are performing EMS interventions. Leveraging state-of-the-art deep learning networks and appropriate real-time algorithms, we can process these sensor data for automated classification of different EMS interventions and assessment of quality for each hand operated activity. Previous research [4, 5] has addressed finger and hand motion detection using sensor data from different sources. However, the EMS domain remains unexplored for the usability of smartwatch based sensor data for activity detection and monitoring. Our goal is to separate the interventions of interest from regular hand movements and provide automated quality assessment with real-time parameter prediction. This will greatly benefit the EMS training procedure, and improve the real-scene application. Figure 1 shows an overview for the problem and our proposed solution.

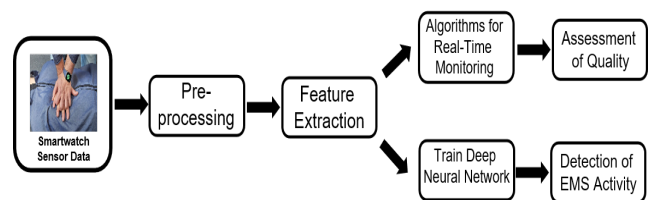
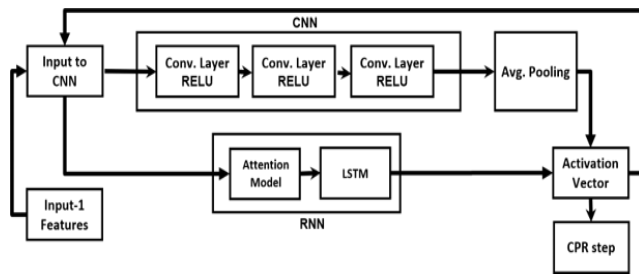


Figure 1: Overview of using smartwatch based sensor data for hand operated activity monitoring in EMS

## 2 PROPOSED SOLUTION

To facilitate automated and improved learning experiences during the training, and better performances in real-EMS scenes for the EMS providers, SenseEMS will use smartwatch based sensor data

for the detection and quality assessment of the following EMS activities: (i) CPR compressions - rate and depth, and (ii) attaching defibrillation pads and/or breathing bags. Currently, we are focusing on CPR compression detection from various hand operated interventions, and real-time rate estimation for CPR for assessment of CPR quality. For this research, we are using Samsung Galaxy Smartwatch5 and Asus Zenwatch2 models for collecting data from accelerometer, gyroscope, and magnetometer sensors. We use an android app WaDa[2] to collect the sensor data. The sensor readings are collected with timestamps throughout the event at 50Hz sampling rate. Before processing, several statistical features are extracted from the data. Each of the sensors provides data signals along the X, Y, and Z axes. We pass the raw signals through a finite impulse response filter to remove the high-frequency vibration noises. Statistical features are generated from each window, i.e., the mean, standard deviation, kurtosis, and skew feature.

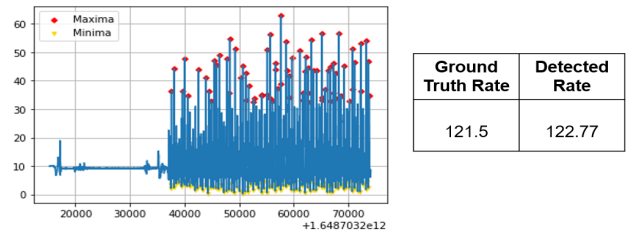


**Figure 2: A hybrid attention model with deep neural network for EMS activity (CPR) detection**

For detecting the CPR rate, SenseEMS is currently using dispersion based peak detection using Z-score on the standard deviation feature. CPR rate is calculated from the average time between consecutive peaks. For classifying CPR compressions, the features will be fed to a hybrid learning model which is a parallel combination of CNN and RNN [4]. The parameters of the model will be chosen based on a preliminary evaluation on a validation set of our overall sensor dataset. Combination of CNN and RNN will allow capturing the spatial and temporal correlation present in input sensor data. As a result, the combination of these two networks will identify the continuous CPR compressions with high accuracy. Currently, our model is testing the gesture detection for compression. A complete compression cycle consists of following two gestures- (i) compression on chest via downward movement of palm(s) for specific time and depth, and (ii) upward rebound for specific time and height. Using the proposed hybrid network, SenseEMS will combine the gestures to classify a continuous compression activity. Figure 2 shows the high level architecture of the classifier model.

### 3 PRELIMINARY RESULTS

Figure 3 shows our primary results for CPR rate estimation using accelerometer data and peak detection algorithm. Table 1 shows our preliminary accuracy of SenseEMS for compressions gesture detection against other techniques. SenseEMS records highest average F-1 score of 90% for our current test dataset, compared to other solutions based on bidirectional LSTM [6] and SVM [5] based networks. This result only highlights the basic gesture detection. We



**Figure 3: CPR rate estimation based on Accelerometer data**

**Table 1: Different methods for hand gesture detection**

| Metric/Tools | bi-LSTM | SVM  | SenseEMS |
|--------------|---------|------|----------|
| Precision    | 0.88    | 0.84 | 0.92     |
| Recall       | 0.87    | 0.79 | 0.89     |
| F-1          | 0.87    | 0.81 | 0.90     |

are currently working on combining the gestures for compressions classification from continuous sensor stream.

## 4 CONCLUSION

SenseEMS is an ongoing project which presents a smartwatch retrieved sensor data based method for hand activity detection and monitoring in Emergency Medical Systems (EMS). Using an attention based hybrid deep neural network for detecting patterns in hand operated intervention, and suitable real-time algorithms on the extracted features, SenseEMS will provide real-time and post-scene classification and quality assessment for EMS hand operated activities during the training and real-scenes. Surveying 31 anonymous EMS providers on SenseEMS reveals a potential influence of the ongoing research in EMS domain.

## ACKNOWLEDGMENTS

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## REFERENCES

- [1] Jonathan Hobbs. 2020. It is time to rethink EMS. *The Veterinary Record* 187, 9 (2020), 363–364.
- [2] Md Abu Sayeed Mondol, Ifat A Emi, Sirat Samyoun, M Arif Intiazur Rahman, and John A Stankovic. 2018. WaDa: An Android Smart Watch App for Sensor Data Collection. In *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*. 404–407.
- [3] Sarah Masud Preum, Sirajum Munir, Meiyi Ma, Mohammad Samin Yasar, David J Stone, Ronald Williams, Homa Alemzadeh, and John A Stankovic. 2021. A review of cognitive assistants for healthcare: Trends, prospects, and future directions. *ACM Computing Surveys (CSUR)* 53, 6 (2021), 1–37.
- [4] Sirat Samyoun, Sudipta Saha Shubha, Md Abu Sayeed Mondol, and John A Stankovic. 2021. iWash: A smartwatch handwashing quality assessment and reminder system with real-time feedback in the context of infectious disease. *Smart Health* 19 (2021), 100171.
- [5] Hongyi Wen, Julian Ramos Rojas, and Anind K Dey. 2016. Serendipity: Finger gesture recognition using an off-the-shelf smartwatch. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. 3847–3851.
- [6] Peide Zhu, Hao Zhou, Shumin Cao, Panlong Yang, and Shuangshuang Xue. 2018. Control with gestures: A hand gesture recognition system using off-the-shelf smartwatch. In *2018 4th International Conference on Big Data Computing and Communications (BIGCOM)*. IEEE, 72–77.