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Online Multi-Task Learning and Wearable Biosensor-based Detection of Multiple Seniors' Stress in Daily Interaction with the Urban Environment

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Abstract: Wearable biosensors have the potential to non-invasively and continuously monitor seniors' stress in their daily interaction with the urban environment, thereby enabling to address the stress and ultimately advance their outdoor mobility. However, current wearable biosensor-based stress detection methods have several drawbacks in field application due to their dependence on batch-learning algorithms. First, these methods train a single classifier, which might not account for multiple subjects' different physiological reactivity to stress. Second, they require a great deal of computational power to store and reuse all previous data for updating the signle classifier. To address this issue, we tested the feasibility of online multi-task learning (OMTL) algorithms to identify multiple seniors' stress from electrodermal activity (EDA) collected by a wristband-type biosensor in a daily trip setting. As a result, OMTL algorithms showed the higher test accuracy (75.7%, 76.2%, and 71.2%) than a batch-learning algorithm (64.8%). This finding demonstrates that the OMTL algorithms can strengthen the field applicability of the wearable biosensor-based stress detection, thereby contributing to better understanding the seniors' stress in the urban environment and ultimately advancing their mobility.

Key words: Online multi-task learning, wearable biosensing, stress in daily life, seniors' mobility, the urban environment

1. INTRODUCTION

Mobility (i.e., an individual's overall capability to access desired people or places [1]) is a fundamental civil right that should be maintained in the urban infrastructure [2]. However, the mobility of the senior population (i.e., people aged 65 or over) has been significantly limited mainly due to the stressful interactions with the current urban infrastructure that they suffer in their daily trips [3-5]. While seniors' physical and cognitive capabilities are impaired as a result of the natural aging process [6], many environmental barriers in the current urban infrastructure, such as steep uphill climbs, curbs without ramps, and complex traffic signage, pose excessive physical or cognitive demands on seniors, thereby inducing stress in their daily trips [3-5]. As a result, several indices of mobility such as frequency and distance of daily trips represent limitations in seniors' mobility [7]. Such limited mobility has caused diverse social issues related to seniors' health and social engagement [8-11].

To monitor and address the seniors' stress in their daily interaction with the built environment, previous approaches have mainly relied on manual surveys [12-14]. Although these survey-based approaches have contributed to identifying different types of the environmental barriers that seniors self-report, they might be limited in field applicability for several reasons. First, these methods require seniors' active participation (e.g., attending surveys and self-reporting), thereby interfering with their daily lives. Also, the survey-based methods are generally conducted in a discontinuous and periodic manner with an interval (e.g., once a half year or once a year) so that may miss a number of environmental barriers that are time-dependent (e.g., snowy sidewalks and rain puddles on streets).

Recent advancements and the prevalence of wearable biosensors can open a door toward a new urban sensing that monitors people's stress in their daily trips. Wearable biosensors can be used as a means to less-invasively and continuously measure stress because human sympathetic nervous system aroused by the stress introverts several physiological activities such as eccrine sweat production and cardiac activity, which could be measured using physiological signals (e.g., electrodermal activity [EDA], skin temperature and photoplethysmogram) [15]. In this sense, several recent studies have proposed to apply wearable biosensors to understand people's stress in their daily lives such as driving [16-18], office work [19], field work [20], and walking [21,22]. To understand stress based on physiological signals collected by wearable biosensors, the previous studies trained and validated a machine learning classifier. Although these studies showed that wearable biosensors could be applied to identify people's stress in a naturalistic setting, there are several limitations. First, these studies applied batch-learning algorithms to create one single classifier to detect different subjects' stress [23]. Given that wearable biosensors would be applied to thousands of citizens as an urban sensing mechanism, one classifier may not be able to accurately detect the numerous citizens' stress because people's physiological response to stress can vary among individuals with different characteristics (e.g., ages, gender, body metabolism, etc.) [24]. Also, batch-learning algorithms store and use all the previous data to update the single classifier every time new data arrives, which will not be computationally practical for an urban sensing context due to a large number of subjects.

To overcome these limitations, the authors apply online multi-task learning (OMTL) algorithms [25,26]. Unlike the batch-learning algorithms that train one single classifier for the entire dataset, OMTL algorithms train multiple classifiers corresponding to the number of tasks in the dataset. At every input of each data point, OMTL algorithms update parameters of classifiers as well as the task interaction matrix that contain information about different tasks' similarity [27]. Specifically, once a data point is input from a task, OMTL algorithms first update the parameters of a classifier trained for the task. Then, other classifiers are also updated based on the input data point having similarity with the task classifier as a learning rate, which could be acquired from the task interaction matrix. The final step is to update the interaction matrix based on the similarities between newly updated parameters of different classifiers. Since OMTL algorithms learn multiple classifiers for each task (each subject in this study), more accurate detection of stress for multiple subjects can be expected. Also, the OMTL algorithms are basically the online learning algorithms that update classifiers at every input of data points. Therefore, there is no need to store and use all the previous data to update classifiers for newly arrived data. However, the feasibility of OMTL algorithms to understand people's stress from physiological signals collected by wearable biosensors in a daily trip setting has not been well studied. Although a recent study tested the OMTL algorithms to understand construction workers' stress [28], this study used the brainwave data collected by wearable-type electroencephalography sensor (EEG) that might not be applicable to people's daily lives. To fill the gap, the objective of this study is to test the feasibility of the OMTL algorithms to detect multiple seniors' stress from physiological signals collected by a less-invasive wristband-type biosensor.

2. OMTL-BASED SENIORS' STRESS DETECTION

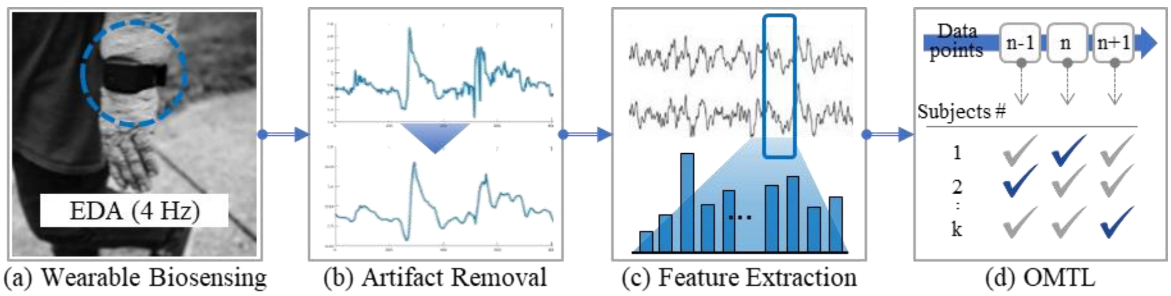

Figure 1. Steps of the OMTL and wearable biosensor-based stress detection for multiple seniors

Figure 1 shows a procedure of the OMTL and wearable biosensor-based stress detection for multiple seniors. First, multiple senior individuals' physiological signals were collected using a wristband-type biosensor. Then, noises contained in the collected physiological signals were alleviated by applying the moving average and high-pass filter. After reducing physiological signal noises, several features were extracted in time and frequency domain to understand patterns of physiological signals. Finally, several OMTL algorithms were applied to train a model to predict multiple different seniors' stress. A more detailed explanation of each step is given below.

2.1. Wearable biosensing

As the first step, multiple senior individuals' physiological signals were acquired using a wristband-type biosensor. The authors collected EDA to measure seniors' stress. EDA shows the changes in electrical conductance of the skin in response to eccrine sweat gland activity [24]. Since eccrine sweat gland is a representative organ that well reflects arousal in sympathetic nervous system induced by stress, the EDA has been widely used to measure human stress. Also, EDA could be continuously and less-invasively collected from people's skin in daily trip contexts.

2.2. Artifact removal

Acquired EDA from uncontrolled and ambulatory settings contains several noises such as noises that come from subjects' body movements and electromagnetic fields [24,29]. Since such noises could compromise the accuracy of detecting stress by distorting values of extracted features from EDA, noise removal is a critical step for accurate detection of stress [30]. The authors applied a moving average filter to remove high-frequency noises such as noises resulting from body movements and surrounding electromagnetic fields [20]. A high-pass filter with the cut-off frequency of 0.05 Hz was also applied to suppress high-frequency noises (e.g., noises caused by variation in temperature, humidity, and impedance of sensor's electrodes) [33].

2.3. Feature extraction

To extract features, EDA was decomposed into two components-electrodermal level (EDL) and electrodermal response (EDR). EDL is a slowly changing component that includes spontaneous fluctuations of EDA [24]. Contrarily, EDR is a fast-changing component that reflects immediate body response to stress [24]. Features were extracted from both EDL and EDR [24]. As a second step, the continuous EDL and EDR were segmented into data points by a window of ten seconds length with one second moving spans. Ten-second window size was selected due to the reactivity of EDA to stress generally spans ten seconds including a latency period [20]. Eleven time domain features and three frequency domain features were extracted from segmented EDL and EDR. In this research, the features were selected from the literature on EDA-based stress identification [21,23,32,33] (Table 1). Specifically, three traditional statistics (i.e., mean, median, and standard deviation) were selected to describe the statistical characteristics of each data segment [21,23,32]. Also, three morphological features (i.e., Integral, Power, and Normalized root mean square) were defined for characterizing the signal wave shape using the following three equations (Equation 1-3) [23,32]. Two features (i.e., mean and variability of intensity overall phasic width) were also extracted to understand EDR's morphology using sparse representation [34]. The sparse representation technique decomposes EDR into multiple atoms from a pre-designed dictionary that well reflects the specific shapes of stress response in EDR [34]. In addition, three spectral power features were used to understand the different patterns in frequency domain according to the different levels of stress [23,32].

$$\text{Integral} = \sum_{n=1}^{N} edr(n) \tag{1}$$

$$\text{Power} = \frac{1}{\text{n}} \sum_{n=1}^{N} edr^2(n) \tag{2}$$

$$\text{Normalized root mean square} = \left(\frac{1}{\text{n}} \sum_{n=1}^{N} edr^2(n)\right)^2 \tag{3}$$

Table 1. The features extracted from EDA

Component	Type	Features
EDL	Time feature	Mean, Median, SD
EDR	Time feature	Mean, Median, SD, Integral, Power, Normalized root mean square, Mean intensity overall phasic width, Variability of intensity overall phasic width
	Frequency feature	Spectral power (0.1 to 0.2 Hz), Spectral power (0.2 to 0.3 Hz), Spectral power (0.3 to 0.4 Hz)

2.4. OMTL

The authors applied all OMTL algorithms developed to date (i.e., OMTL-LogDet, OMTL-von Neumann, and OMTL-Covariance [25,26]) to identify multiple different seniors' stress from EDA. The three OMTL algorithms have different rules for updating the interaction matrix. Here, different subjects were considered as different tasks. For benchmarking purpose, the authors compared the performance of the OMTL algorithms with two baselines. The first baseline was a traditional batch-learning algorithm. Gaussian support vector machine (GSVM) was used as the batch-learning algorithm because GSVM has demonstrated the best performance in detecting stress based on physiological signals collected by a wearable sensor in previous studies [35-37]. The authors applied GSVM in an online setting (repeat updating a classifier based on all the previous data at each input of data point) to compare its performance with OMTL algorithms. By comparing OMTL algorithms with GSVM, it would be examined whether training multiple different classifiers according to different tasks can more accurately detect stress than training one single classifier. The second baseline is the *K* independent task classifiers (ITL) where *K* different classifiers are trained according to different tasks unlike batch-learning algorithms, but there is no cross update between classifiers based on a similarity between tasks. Comparison between ITL and OMTL algorithms can show the benefits from cross update between classifiers of similar tasks.

Table 2 shows the pseudocode of the tested OMTL algorithms. OMTL algorithms jointly update parameters of classifiers (w_t) and task relationship matrix (A_t). First, $A_{t=0}$ and $w_{t=0}$ are initialized (1 in Table 2). Then, when a new data point arrives, its label is estimated using w_t (2 in Table 2). Once the estimation fails, parameters of all classifiers (w_t) are updated considering the task interaction matrix (A_t) (3a in Table 2). Then, A_t is also updated based on the newly updated w_t (3b in Table 2). The update of A_t starts after waiting for a number of rounds, which is determined based on *Epoch* because of the parameter w_t are not well formed during the initial rounds, which lead to poor estimates of A_t.

Table 2. Pseudocode of OMTL algorithms

1. $A_{t=0} = \frac{1}{K} * I_{K\times K}$ and $w_{t=0} = 0_{1\times Km}$ and $t = 0$ 2. $\mathrm{L}(x_t, k_t) = Sign(w_{t,k_t}^T x_t)$ 3. If $\mathrm{L}(x_t, k_t) \neq y_t$ a. $w_{t,i} = w_{t-1,i} + y_t A_{i,k_t}^{-1} x_t \ \forall i \in \{1,2,\cdots,K\}$ b. If $t \geq Epoch \times n$, then update A_t using (1), (2), (3) c. Else, $A_t = A_t$ 4. Else, $w_{t,i} = w_{t,i} \ \forall i \in \{1,2,\cdots,K\}$ and $A_t = A_t$ 5. $t = t + 1$	K: the number of tasks x_t: data point at time t k_t: task of data point at time t y_t: true label of data point at time t $w_t = [w_{t,1}, w_{t,2}, \cdots, w_{t,K}]$: parameters for all classifiers n: number of total data points

The authors applied three OMTL algorithms with different rule of updating task interaction matrix (A_t) as illustrated in equations (1)-(3). There are two parameters of OMTL algorithms, *Epoch* and learning rate. *Epoch* indicates the rate of waiting rounds before updating A_t. η denotes the learning rate for the A_t update. In this study, *Epoch* and η were optimized by 0.6 and $10^{-15.5}$ respectively based on the prior experimental results.

1. OMTL-LogDet: $A_t = \left(A_{t-1}^{-1} + \eta(w_{t-1}^T w_{t-1})\right)^{-1}$, η: learning rate (1)

2. OMTL-von Neumann: $A_t = \exp(\log(A_{t-1}) - \eta w_{t-1}^T w_{t-1})$, η: learning rate (2)

3. OMTL-Covariance: $A_t = \mathrm{cov}(w_{t-1})$ (3)

The test accuracy was compared among all applied algorithms. Specifically, the dataset was first undersampled for balance between classes. When the EDA data are imbalanced, which means that the number of data points in a class is much more than that of other class, the resultant classifier would be inaccurate to predict the minority class. Random permutation was also conducted because the input order of data points could affect the test accuracy. Then, the permuted dataset was randomly divided into 80% training session and 20% testing session without any overlap. All the tested algorithms were applied to train and update classifiers using data points sequentially taken from the training session. At every input of each data point, the updated classifiers' test accuracy was measured based on the testing session. After completing the update using all the data points, the test accuracy was averaged. This 'undersampling-permutation-holdout test' procedure was repeated 20 times and reported test accuracy was calculated by averaging the 20 trials to make sure that the results reflected the general performance of the tested algorithms, not the performance in a randomly undersampled, generated and permuted subset of data.

3. FIELD DATA COLLECTION

The ten mobile senior subjects were recruited for the field data collection from Clark East Tower senior apartment located in Ypsilanti Township, Michigan. Data collection protocol was approved by the University of Michigan Institutional Review Board (IRB00000245). The informed consent forms were distributed to make all the subjects informed about the anonymity of data collection and their rights. They were also asked to report their mental health issues. None of the subjects reported any mental issues that can affect stress detection based on physiological signals. To account for variability of senior population in physical capability, five seniors depending on a walker or scooter as an assistive device were included in the subject group. Table 3 summarizes the subjects' demographic information.

Table 3. Subjects' Demographic Information

Item	Age (years)	Height (cm)	Weight (kg)	Assistive Device Use
Mean (SD)	68.1 (5.79)	168.3 (8.7)	81.7 (8.4)	Walker 4, Scooter 1, No use 5

In the field data collection, the subjects were asked to walk over a predesigned route on which there was a series of 12 environmental barriers, including curbs without ramps and unpaved sidewalks (Figure 2). The series of environmental barriers were determined by authors based on previous studies that identified the typical environmental barriers where seniors get stressed in the current urban infrastructure [4,39]. While the subject passed along the route, their EDA signal was collected at 4 Hz sampling rate using a wristband-type biosensor. During the experiment, participants were video recorded for labeling purposes. After subjects completed the route, the researchers surveyed whether the subjects actually became stressed or not on each environmental barrier in a binary manner (i.e., stress or non-stress). To reduce the recall bias, the authors showed pictures of all the environmental barriers. After the data collection, the collected EDA signals were labeled into stress or non-stress based on the result of the stress survey as well as the recorded video. The authors excluded EDA signals collected when the subjects experienced unintended stressors such as interaction with vehicles or other people and loss of balance while walking. Then, EDA signals acquired while subjects passed over environmental barriers that they confirmed as a stressor in the survey were labeled as "stress."

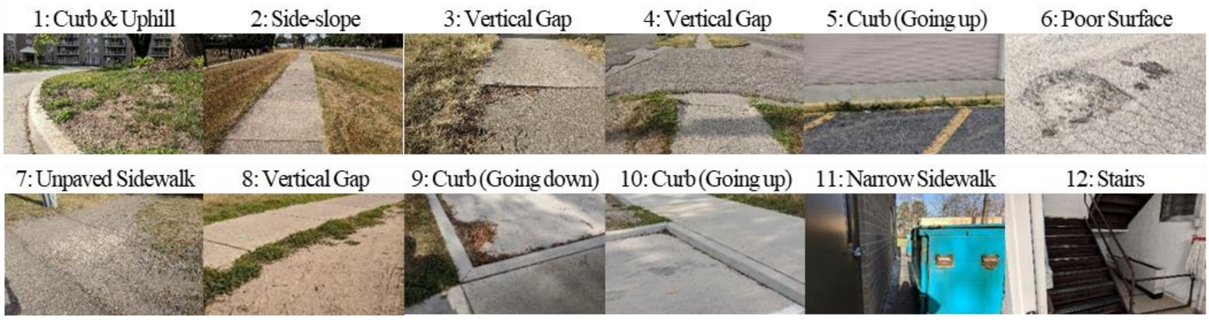

Figure 2. Environmental barriers in data collection

4. RESULTS AND DISCUSSIONS

As a result of field data collection, 23,627 data points were collected. Among them, 1,936 data points were labeled as stress, and other 21,691 data points were labeled as non-stress. Due to such imbalance, balanced 3,872 data points (the whole 1,936 stress data points, and 1,936 undersampled non-stress data points) were generated by undersampling as a first step of the 'undersampling-permutation-holdout test' procedure. The confusion matrices for different algorithms are reported in Table 4. Three performance metrics were used: accuracy, precision, and recall. Accuracy indicates the tested algorithms' overall performance to correctly classify whole samples. Precision means the performance to exclude actual "non-stress" samples from "stress" class, while recall is the performance to include actual "stress" samples in "stress" class.

The batch-learning algorithm (GSVM) showed the lowest test accuracy (64.8%). Compared with the batch-learning algorithm, ITL performs better with a prediction accuracy of 70.6%. This result shows that independently training ten different classifiers for ten different subjects will lead to more accurate stress detection. This may be explained by the fact that the one classifier trained by the batch-learning algorithm could not enough account for the ten subjects' different physiological reactivity to stress.

Table 4. Confusion matrices of the tested algorithms

		Batch-learning (GSVM)			
Accuracy: 64.8%		True Class		Precision	Recall
		High Risk	Low Risk		
Predicted Class	High-Risk	28.2%	13.7%	67.4%	57.1%
	Low-Risk	21.8%	36.3%		
		Independent Task classifiers (ITL)			
Accuracy: 70.6%		True Class		Precision	Recall
		High Risk	Low Risk		
Predicted Class	High-Risk	39.6%	18.7%	68.0%	78.7%
	Low-Risk	10.7%	31.0%		
		OMTL LogDet			
Accuracy: 75.7%		True Class		Precision	Recall
		High Risk	Low Risk		
Predicted Class	High-Risk	38.3%	12.0%	76.2%	75.6%
	Low-Risk	12.4%	37.3%		
		OMTL von-Neumann			
Accuracy: 76.2%		True Class		Precision	Recall
		High Risk	Low Risk		
Predicted Class	High-Risk	38.2%	11.9%	76.2%	76.3%
	Low-Risk	11.9%	38.0%		
		OMTL Covariance			
Accuracy: 71.2%		True Class		Precision	Recall
		High Risk	Low Risk		
Predicted Class	High-Risk	39.4%	18.0%	68.6%	78.5%
	Low-Risk	10.8%	31.8%		

All the applied OMTL algorithms brought higher test accuracy (75.7% for OMTL-LogDet, 76.2% for OMTL-von Neumann, and 71.2% for OMTL-Covariance) than both ITL and the batch-learning algorithm. It indicates that cross update between different classifiers, which the OMTL algorithms conducted based on the similarity between their tasks, helps train all the classifiers, thereby bringing better test accuracy than training each classifier independently. Among different OMTL algorithms, test accuracy of the OMTL von-Neumann and OMTL LogDet were higher (76.2% and 75.7% respectively) than OMTL Covariance. This result coincides with the result of [28], which applied OMTL to detect stress based on EEG signals. Given that OMTL Covariance showed comparable performance to other OMTL algorithms in tasks using text data [26], the better performance of OMTL von-Neumann and OMTL LogDet in this study may be because of the more robust performance of these two algorithms when dealing with outliers in physiological signals such as EDA and EEG due to the exponential and reciprocal updating [28].

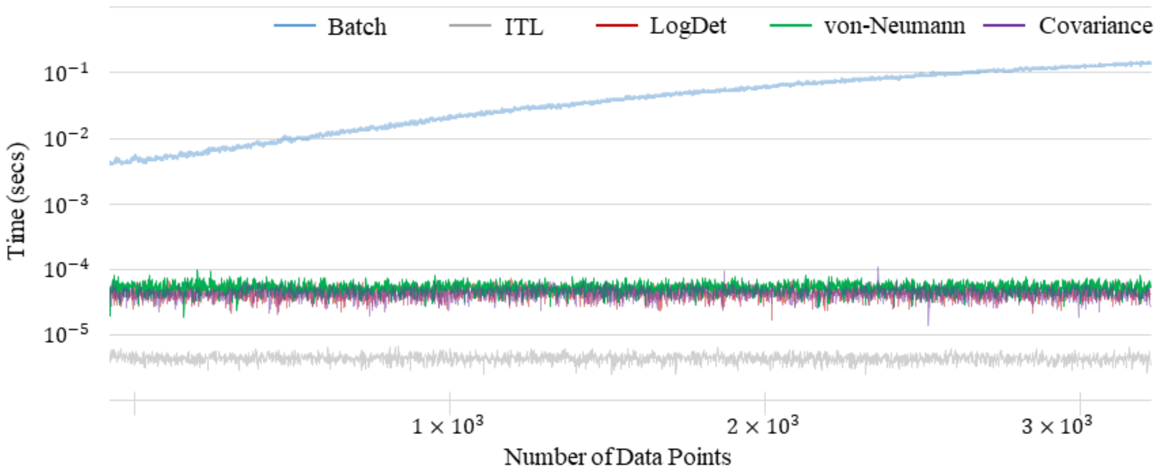

Figure 3. Computational time of tested algorithms

In addition to accuracy, all the tested algorithms' computational time was examined to compare computational complexity. Figure 3 shows the computational time of every update. The reported computational time was calculated by averaging 20 times of trainings. As a result, the traditional batch learning algorithm in an online setting spent significantly higher computational time than the OMTL algorithms and ITL. Also, the batch learning algorithm's computational time increased with every update while those of OMTL algorithms stayed within a certain range. This can be explained by the fact that the batch learning algorithms require all the previous data points for each update, and the number of data points in the batch increased by one at every update. Given that data size in urban sensing contexts is, in general, far bigger than the data collected in this study, such increase in computational complexity according to the number of data points indicates that the batch learning algorithms might be less practical in urban sensing contexts. ITL showed the least computational complexity, which can be expected because ITL does not update interaction matrix unlike OMTL algorithms. There was no significant difference among OMTL algorithms.

The results of this study indicate that the OMTL algorithms can more accurately detect multiple seniors' stress from EDA collected by a wristband-type biosensor in a daily trip setting than traditional batch-learning algorithms. Also, OMTL algorithms showed less computational complexity than the traditional batch learning algorithm. Since the OMTL algorithms do not need to store and use all previous data for updating their classifiers, they are less computationally complex than traditional batch-learning algorithms. Lower computational cost and time of these algorithms make them a better fit for the urban sensing to extensively identify seniors' stress in the urban environment.

Finally, a number of important limitations need to be considered. First, the simple perceptron was used for as a base learning algorithm (3a in Table 2) in the OMTL algorithms in this study. More sophisticated parametric algorithms such as the kernel perceptron have been developed to train a classifier in an online setting [39]. The future studies will additionally apply such algorithms for the classifier update to increase the performance of OMTL algorithms. Second, this study was conducted based on a small sample of senior population (i.e., 10 subjects). Given that the stress detection would be applied in urban scale, how the proposed OMTL-based stress detection performs with a larger sample of senior population needs to be examined in a future study. Specifically, the sample of senior population should exhibit considerable variability in age, physical conditions, and assistive device use to make sure generalization of the proposed stress detection. Third, although only different subjects were dealt as different tasks in this study, different outdoor conditions such as temperature and a level of humidity should be considered as different tasks as well because EDA signal's reactivity to stress varies according to such outdoor conditions [24]. Future research is needed to examine whether OMTL algorithms can accurately detect stress under different outdoor conditions as well as different subjects. Lastly, although OMTL algorithms can significantly improve the practicality of wearable-based stress detection by working without storing and using all the previous data, still data from all users needs to be labeled, which is another critical hurdle to apply wearable-based stress detection in urban sensing contexts. To address the labeling burden, how stress detection models can be applied for a new person who is not involved in training should be studies in future research.

5. CONCLUSION

The traditional batch-learning algorithms could not be applied for the urban sensing to detect thousands of seniors' stress in daily trips because they depend on one classifier and require much computational power to store and re-use all the previous data for updating the classifier. To address this issue, the authors tested the feasibility of OMTL algorithms to detect stress based on different seniors' EDA signals collected by a wearable biosensor in a daily trip setting. Specifically, EDA signals labeled as stress or non-stress were collected from ten senior subjects while experiencing a predesigned route on which there was a series of environmental barriers. Based on the EDA signals, the test accuracy of three OMTL algorithms were compared with a traditional batch-learning algorithm (i.e., GSVM). As a result, all OMTL algorithms showed higher test accuracy (75.7% for OMTL-LogDet, 76.2% for OMTL-von Neumann, and 71.2% for OMTL-Covariance) than the batch-learning algorithm (64.8%). This result indicates that the OMTL algorithms are more feasible than the batch-learning algorithms to accurately detect multiple seniors' stress in an online manner based on EDA collected by wearable biosensors in a daily trip setting. This finding can improve the field applicability of the wearable biosensing-based stress monitoring method, thereby contributing to monitoring and addressing seniors' stress in their daily trips, and ultimately advancing their outdoor mobility.

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