A Metric Learning Approach for Personalized Meal Macronutrient Estimation from Postprandial Glucose Response Signals

Michael Yang, Projna Paromita, Theodora Chaspari, Anurag Das, Seyedhooman Sajjadi, Bobak J. Mortazavi, and Ricardo Gutierrez-Osuna
Computer Science and Engineering, *Texas A&M University*, College Station, USA
{michael.yang, projna.paromita, chaspari, adas, hooman130, bobakm, rgutier}@tamu.edu

***Abstract*—Managing diabetes requires following a healthy lifestyle, including monitoring dietary intake. Prior work has shown that meals with different macronutrient composition can have distinct postprandial glucose responses (PPGR), therefore suggesting that PPGRs may be used to monitor diet automatically. Yet, PPGRs shown large variability across individuals. This paper proposes a metric-learning approach to achieve personalized meal macronutrient estimation from PPGRs. The metric learning approach utilizes a Siamese neural network (SNN) architecture, which learns a PPGR embedding via a contrastive loss function adapted to the task of interest. Specifically, the proposed contrastive loss is designed so that it maximizes the distance between meals of similar macronutrient composition and minimizes the distance between meals with different macronutrients. This loss is further computed within each individual, therefore reducing individual differences in PPGRs. Our results show that the proposed metric learning approach outperforms a feedforward neural network when estimating the amount of protein, carbohydrate, and fat in a meal. These suggest the feasibility of using PPGRs to track meal macronutrient composition, supporting dietary informatics applications for precision health and nutrition.**

***Index Terms*—Diabetes mellitus, personalized diet tracking, postprandial glucose response, metric learning, siamese network**

I. Introduction

Diabetes mellitus (DM) is a heterogeneous metabolic disorder [1] with increasing prevalence that is intensified by sedentary lifestyles, carbohydrate-rich diets, and lack of awareness [2], [3]. Diabetic patients suffer from irregular blood glucose levels [1], which over time can increase the risk of other diseases (e.g., cardiovascular disease, neuropathy) [3]. Leading a healthy lifestyle and consuming a balanced diet is essential to preventing or controlling DM [3].

Continuous glucose monitors (CGM) record postprandial glucose responses (PPGR) at regular intervals over an extended period of time. CGMs measure glucose in the interstitial fluid, which is subsequently transmitted and stored in mobile devices and servers for further analysis [14]. Collecting PPGRs and other contextual information (e.g., meal intake, physical activity) can provide valuable insights for properly managing diet and avoiding extreme glycemic events. Previous work has used CGMs to predict PPGRs in response to food intake [8], [15], predict hyperglycemic and hypoglycemic events [16], and estimate the type and macronutrient composition of a meal [17]–[20]. PPGRs depict distinct patterns in response to different meals. For instance, meals that are rich in carbohydrates lead to sharp increases in PPGR with high peak [11], whereas meals rich in protein or fat do not reflect such a drastic change, yielding lower and potentially wider PPGR peaks [12]. Such observations can serve as the foundation for diet monitoring applications based on PPGR data.

However, the shape of the PPGR is influenced by multiple factors, such as patients' anthropomorphic features, metabolic characteristics, lifestyle, and physical activity. Thus, PPGRs exhibits large inter-individual variability [8], [9]. This calls for the design of models that can effectively reduce the effect of patient-specific information in the PPGRs, while retaining information related to the macronutrient composition. Toward this goal, Sajjadi *et al.* investigated three types of standardization techniques, including baseline correction, feature normalization, and integrating information about participants' anthropometric characteristics [19]. Paromita *et al.* further proposed a metric learning technique to account for the large inter-individual differences in PPGRs for the purpose of meal classification [17]. In the same study, anthropometric and metabolic characteristics were further considered as an additional input to the machine learning models in combination with the PPGR itself. Results from both studies demonstrate the importance of accounting for inter-individual differences in PPGRs in order to make it possible ot monitor diet automatically with CGMs [17], [19].

In this paper, we propose a metric learning approach to tackle the large inter-individual variability in PPGR, for the purpose of personalized estimation of meal macronutrients. The proposed metric learning approach models the relative difference of PPGRs between different meals within an individual through a Siamese neural network (SNN). The SNN takes a pair of PPGRs from the same participant as an input and learns a transformation of the PPGR (i.e., a PPGR embedding) via a contrastive loss function appropriately designed for the task of interest. According to the proposed contrastive loss, pairs of samples corresponding to meals with proximal macronutrient composition are projected to the same neighborhood of the PPGR embedding, while the opposite occurs for samples with distinctively large difference in their composition. In this way, the distance between the PPGR embedding learned by the SNN is a function of the difference in macronutrient composition of the corresponding pairs of samples. Our approach is evaluated on 15 healthy participants, who consumed 9 standardized meals with different composition of carbohydrates, proteins, and fats. Results indicate that metric learning can estimate meal macronutrients whith higher accuracy than a comparable feedforward network, achieving Pearson's correlation of 0.55, 0.42, and 0.55 between ground truth and prediction of carbohydrates, proteins, and fats, respectively.

II. Prior Work

Recent work has examined the potential of utilizing PPGRs collected via CGM devices for meal monitoring purposes. Huo *et al.* designed a multitask neural network to estimate the macronutrient composition of a meal [20]. Das *et al.* proposed a sparse decomposition model for representing PPGR signals for the same purpose [18]. According to this, a new meal was represented as a combination of PPGRs from a set of training samples in a dictionary. To mitigate the large inter-individual variability in PPGRs and reduce subject dependencies, Sajjadi *et al.* explored three different techniques, including baseline correction of the PPGR, normalization of the PPGR feature space, and integration of antrhopometric features in the machine learning models [19]. Paromita *et al.* further used a metric learning approach to reduce inter-individual differences in PPGRs [17]. This approach learned a transformed glycemic embedding from PPGRs, such that different meals were placed in a large distance apart in the transformed glycemic space, while the opposite occurred for similar meals. This work was evaluated in terms of its performance on classifying between three different meals (i.e., cornflakes and milk, peanut butter sandwich, protein bar), while metric learning has not been formulated for the more complex task of meal macronutrient estimation.

Metric learning has been used with great success in the field of computer vision for the purposes of object classification [21], [27] and tracking [24]. Because of its ability to model the relative distance between input samples (e.g., pairs, triplets), metric learning has shown remarkable performance with a small (or even non-existent) number of training data, in what is known as zero-shot and few-shot learning [27]. In the domain of signal and audio processing, metric learning implemented with a SNN architecture has been effectively utilized to detect acoustic events based on solely a single exemplar target sample [22]. A similar architecture implemented with a triplet loss has been employed in speaker recognition, where audio embeddings for a target speaker were learned using a small number of input samples [28].

The contributions of this research to the existing body of literature are as follows: (1) In contrast to prior work, which investigated distribution-based learning methodologies (e.g., K-nearest neighbor, feedforward neural network (FNN)) that model the absolute patterns of PPGRs in relation to a given macronutrient composition [18]–[20], we examine a metric learning approach for jointly estimating the level of carbohydrate, protein, and fat in a meal from PPGR signals. The proposed metric learning algorithm models the relative difference in PPGRs between pairs of meals, therefore–grounded on evidence from prior work on speech and image processing [21], [25], [27], [28]–has the potential to perform well in our domain of interest. (2) We propose a novel loss function that compares two meals in terms of their macronutrient composition and their distance in the PPGR embedding space. In contrast to implementing metric learning for the purposes of meal classification, the implementation of regression with metric learning is more complex, since we need to define an appropriate loss function that models pairwise distances with respect to both the PPGR embedding space and the continuous label space that describes the macronutrient composition.

TABLE I
Macronutrient composition of standardized meals for carbohydrate, protein, and fat.

Meal ID	Carbohydrate	Protein	Fat
A	c1 (52.25g)	p1 (15g)	f1 (13g)
B	c1 (52.25g)	p2 (30g)	f2 (26g)
C	c2 (94.75g)	p2 (30g)	f1 (13g)
D	c2 (94.75g)	p1 (15g)	f2 (26g)
E	c2 (94.75g)	p2 (30g)	f2 (26g)
F	c2 (94.75g)	p2 (30g)	f3 (52g)
G	c2 (94.75g)	p3 (60g)	f2 (26g)
H	c3 (179.75g)	p2 (30g)	f2 (26g)
I	c3 (179.75g)	p3 (60g)	f3 (52g)

III. Data Description

The dataset used for this study was collected from 15 healthy participants 60-85 years of age, with BMI ranging from 25-35. The study spanned 9 days, in which each participant came to the lab for 8 hours. PPGRs were measured throughout the duration of the study every 15 minutes using a commercial CGM device (Abbott Freestyle Libre Pro). Participants were asked to fast for at least eight hours prior to meal consumption, which gave us the opportunity to observe the fasting blood glucose level before the start of the study. After recording the fasting blood glucose level, participants consumed a standardized meal and were asked to remain sedentary in the lab for the next 8 hours without any additional meal consumption. The standardized meals were administered to each participant at a randomized order and consisted of different levels of carbohydrate (C), protein (P), and fat (F), as described in Table I. The study was approved by the Texas A&M Institutional Review Board (IRB #2017-0886).

IV. Methodology

Here, we will outline the features extracted from the PPGR (Section IV-A). We will further describe the proposed metric learning approach for meal macronutrient estimation (Section IV-B), as well as the baseline models and evaluation methods for the same task (Section IV-C).

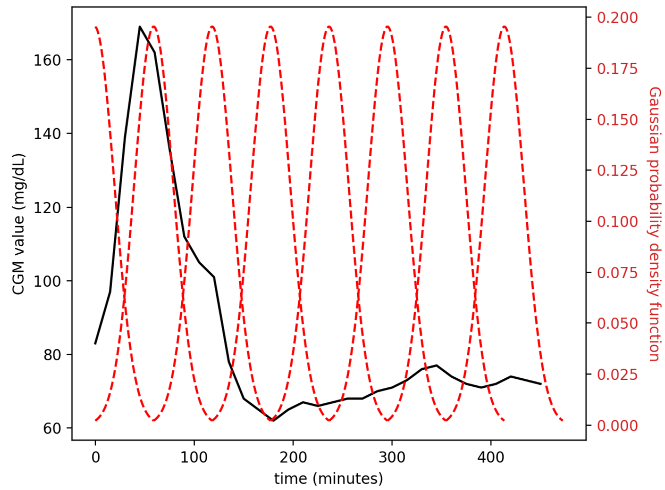

Fig. 1. Family of Gaussian kernels (dashed red line) used to calculate the area under the curve around 8 distinct time points, and example PPGR signal (solid black line).

A. Feature extraction

Baseline correction based on the fasting blood glucose measurements (Section III) was first applied to the collected PPGRs in order to reduce participant-dependent differences with respect to overall glucose levels. The area under curve (AUC) of the PPGR-corrected signals was further calculated at 8 distinct time points equally distributed within the 8-hour analysis window (Figure 1), resulting in 8 total features per PPGR. Then, feature normalization was performed by subtracting the mean of each feature and dividing by its standard deviation, computed within subject. The normalized PPGR features comprised the input to our experiments. This feature extraction approach is similar to prior work [17], [19], [20] and has been found useful for accurately characterizing the PPGR shape.

B. Metric learning of PPGR embeddings

We designed a metric learning algorithm to model the pairwise distance between meals with respect to the PPGR space within each participant. Let i and j be two different meals consumed by a given participant. The PPGR features of the two meals are represented by vectors $\mathbf{x_i} \in \mathbb{R}^8$ and $\mathbf{x_j} \in \mathbb{R}^8$, which correspond to the 8 Gaussian AUC features (Section IV-A). Also let $\mathbf{y_i} \in \mathbb{R}^3$ and $\mathbf{y_j} \in \mathbb{R}^3$ be the macronutrient label of meals i and j, respectively. The label vector is defined as $\mathbf{y} = [c, p, f] \in \mathbb{R}^3$, where $c, p, f \in \{1, 2, 3\}$, depending on whether the corresponding meal has a low (i.e., c1, p1, f1; Table I), medium (i.e., c2, p2, f2; Table I), or high (i.e., c3, p3, f3; Table I) level of carbohydrate, protein, and fat, respectively. For example, the label of meal A is $y_A = [1, 1, 1]$, since it contains a low amount of carbohydrate, protein, and fat, while the label of meal B is $y_B = [1, 2, 2]$, since it is low on carbohydrate and medium on protein and fat (Table I).

Metric learning was implemented via a SNN (Figure 2). The SNN takes as an input the PPGR features $\mathbf{x_i}$ and $\mathbf{x_j}$ from the pair of meals (i, j), and transforms these via a non-linear function $f : \mathbb{R}^8 \rightarrow \mathbb{R}^{16}$, implemented via two fully connected layers with 16 neurons each. The output of the fully-connected layers contains the transformed PPGR feature (i.e., PPGR embedding) $f(\mathbf{x_i}) \in \mathbb{R}^{16}$ and $f(\mathbf{x_j}) \in \mathbb{R}^{16}$ from meals i and j, respectively. We introduce a custom loss function to learn the PPGR embedding f, which ensures that the distance between meals in the PPGR embedding space f (i.e., $f(\mathbf{x_i})$ and $f(\mathbf{x_j})$) is proportional to the corresponding distance in the macronutrient space (i.e., $\mathbf{y_i}$ and $\mathbf{y_j}$), according to the following equation:

$$L_c = \sum_s \sum_{\{i,j\} \in \mathcal{X}_s} \left| \left(d_1(f(\mathbf{x_i}), f(\mathbf{x_j})) - d_2(\mathbf{y_i}, \mathbf{y_j})\right) \right| \quad (1)$$

where $\mathcal{X}_s$ is the set of meal samples from participant s. In (1), d_1 represents the distance of meals i and j with respect to the embedding space via the the $l2$-norm between $f(\mathbf{x_i})$ and $f(\mathbf{x_j})$, and d_2 represents the distance of the two meals with respect to the macronutrient labels via the $l1$-norm between $\mathbf{y_i}$ and $\mathbf{y_j}$. For instance, the distance of meals A and B with respect to the macronutrient space will be $d_2(\mathbf{y_A}, \mathbf{y_B}) = \|[1, 1, 1] - [1, 2, 2]\|_1 = 2$ (Table I).

In addition to modeling the pairwise distance between meals, we further impose another constraint in the proposed SNN architecture, that adds an extra level supervision to the task of interest. We achieve this by learning another transformation $g \in \mathbb{R}^{16} \rightarrow \mathbb{R}^3$ that takes as an input the PPGR embedding $f(\mathbf{x})$ and outputs the label vector $\mathbf{y}$, which contains the carbohydrate, protein, and fat composition. The transformation g is implemented via a fully connected layer, learned using the regression error:

$$L_e = \sum_s \sum_{i \in \mathcal{X}_s} \|\mathbf{y_i} - g(f(\mathbf{x_i}))\|_2^2 \quad (2)$$

where $\mathcal{X}_s$ is the set of meal samples from participant s.

The SNN was trained to minimize the combined contrastive and regression error loss, $L = L_c + L_e$, for 200 epochs using a batch size of 64. A dropout of 0.3 and $l2$ kernel regularization of 10^{-5} were used. ADAM was selected as the optimizer, with an accompanying learning rate of 10^{-3}.

C. Baseline and evaluation method

We used a conventional distribution-based learning, implemented by a FNN, as a baseline method to compare with the proposed metric learning approach. The FNN architecture was chosen to be comparable to the SNN, and comprised of 8 neurons at the input layer, 16 neurons at the subsequent two hidden layers, and 3 neurons at the final regression output layer. As with the SNN, the normalized 8 AUC features (Section IV-A) served as the input to the FNN, and the level of the three macronutrients served as the output. The FNN was trained for 200 epochs with a learning rate of 0.001 and batch size of 16. Mean squared error was used for the loss.

The experiments for both the SNN and baseline FNN were performed using leave-one-participant-out-cross validation. The experiments for both the SNN and FNN were

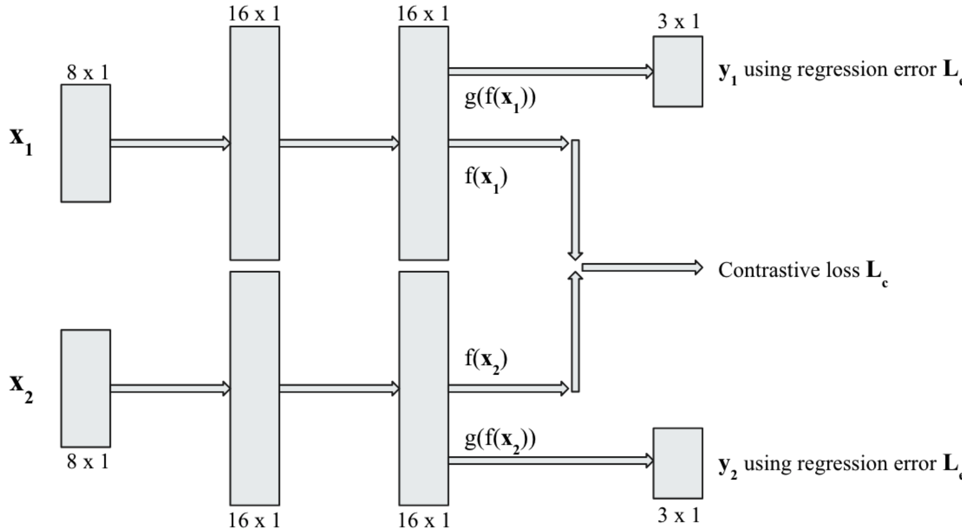

Fig. 2. Schematic representation of the proposed metric learning approach for meal macronutrient estimation implemented with a Siamese network.

TABLE II
NORMALIZED ROOT MEAN SQUARED ERROR (NRMSE) AND CORRELATION VALUES OF MEAL MACRONUTRIENT ESTIMATION VIA METRIC LEARNING (SIAMESE NEURAL NETWORK) AND DISTRIBUTION-BASED LEARNING (FEEDFORWARD NEURAL NETWORK), FOLLOWED BY T-TEST RESULTS COMPARING THE TWO.

Evaluation Metric	**FNN**			**SNN**			**T-test**		
	Proteins	***Carbs***	***Fats***	***Proteins***	***Carbs***	***Fats***	***Proteins***	***Carbs***	***Fats***
Pearson's correlation	0.379*	0.465*	0.510*	0.429*	0.556*	0.571*	t(19)=-4.06*	t(19)=-6.99*	t(19)=-5.18*
Spearman's correlation	0.376*	0.474*	0.458*	0.429*	0.594*	0.556*	t(19)=-4.87*	t(19)=-9.74*	t(19)=-8.22*
Normalized root-mean-square error	0.567	0.524	0.490	0.517	0.453	0.452	t(19)=3.70*	t(19)=4.25*	t(19)=3.04*

*: $p < 0.01$

repeated 20 times. Pearson's and Spearman's correlation were calculated between the estimated and actual value of each macronutrient. Additionally, the normalized root-mean-square error was computed (NRMSE). Paired t-tests were performed comparing the SNN and FNN performance with respect to these metrics. Each t-test compared the corresponding metrics yielding by the 20 repetitions of running the SNN and FNN models.

V. RESULTS

Table II presents the evaluation metrics (i.e., Pearson's correlation, Spearman's correlation, NRMSE; Section IV-C) for the metric learning approach (i.e., SNN) and baseline distribution-based learning (i.e., FNN), as well as the t-test results comparing the two approaches. We observe that the proposed metric learning approach yields significantly higher correlation coefficients and significantly lower NRMSE compared to the baseline distribution-based learning for all three macronutrients. Furthermore, the level of carbohydrates and fat is more accurately estimated compared to the level of protein.

Our results are comparable to prior work, which explored the task of meal macronutrient estimation on the same dataset. The sparse-coding approach proposed in [18] achieved a correlation coefficient of 0.49, 0.28, and 0.39 for carbohydrate, protein, and fat, respectively, therefore yielding a worse performance compared to this paper. However, the combination of macronutrient value normalized through z-score with XGBoost yielded better results (i.e., 0.83, 0.43, and 0.65 for carbohydrate, protein, and fat, respectively). Given that our data is collected in a controlled environment with a participant pool with little variation in demographics, it is reasonable to anticipate good performance from advanced distribution based approaches, such as XGBoost. We anticipate that our proposed approach would be able to better handle the large variability of data and perform equally well in less constrained settings.

Despite the encouraging results, this work presents the following limitations. First, our approach was evaluated on data from a limited number of participants, therefore potentially reducing the generalizability of the study. As the time of this writing, we are in the planning stages for collecting data from 90 participants, which will provide the opportunity to evaluate the proposed algorithm at a larger scale. Second, the data were recorded in a laboratory environment, where we were able to control for confounding factors that can potentially affect PPGRs (e.g., consecutive meals consumed at proximal time points, physical activity). Finally, we employed a conventional distribution-based learning method as a baseline approach to compare our algorithm with. As part of our future studies, we will evaluate the proposed SNN implementation against additional metric learning approaches (e.g., maximum independence domain adaptation [29]).

VI. CONCLUSION

We have proposed a metric learning method to learn subject-independent PPGR embeddings for estimating the macronutrient composition of a meal. Results indicate that our approach outperforms distribution-based learning approaches for the task of predicting the amounts of carbohydrate, protein and fat. As a part of the future work, we will evaluate our algorithm with additional participants in more realistic settings, and examine participants' anthropometric and metabolic characteristics as additional input features.

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