Image2Weather: A Large-Scale Image Dataset for Weather Property Estimation

Wei-Ta Chu
National Chung Cheng University
Email: wtchu@ccu.edu.tw

Xiang-You Zheng
National Chung Cheng University
Email: grapefruit623@gmail.com

Ding-Shiuan Ding
National Chung Cheng University
Email: lzi94u@gmail.com

***Abstract*—To facilitate weather property estimation from images, a large-scale image dataset associated with rich weather information is developed. Through the taken time and geographical information of a photo, we associate it with weather properties obtained from a weather forecast website. Through data filtering like indoor/outdoor classification and sky region detection, a clean and large-scale image-weather dataset (named Image2Weather dataset) consisting of more than 250,000 photos is built to promote related researches. In addition to reporting statistical characteristics of this dataset, we also investigate the relationship between several visual features and weather properties, which then serve as the foundation of interesting applications like weather type classification and temperature estimation. We show effectiveness of weather property estimation based on the Image2Weather dataset, and discuss how it can be leveraged to facilitate related studies.**

I. Introduction

Estimating image properties from visual content is a fundamental step of various computer vision studies. For example, estimating image scene labels [1] [2] facilitates image browsing and retrieval, and recognizing whether images were captured indoors or outdoors [3] facilitates place recognition. Recently, estimating geographic information from images [4] attracts much attention because various potential applications can be expected. In this paper, we advocate an image property that affects visual appearance of images and well perceived by human beings, but has attracted little research attention for a long time: *weather information*.

By analyzing geographical or weather information of user-generated images shared on the web, we could *unveil characteristics in the real world from images available in the cyberspace*. Comparing with geographical information, weather keeps changing even at the same place, and thus we think weather variations across time periods provide richer information and give impact to wider fields. For example, by estimating weather information from images uploaded by users, the population's cameras can be viewed as weather sensors, and fine-grained weather monitoring can be achieved. Coupling estimated weather information with time/geographical information, explicit or implicit human behaviors can be discovered. For example, more people travel (and thus more photos taken) on weekends if it is sunny, and some places are especially attractive if the temperature is under $-5°$C. Weather information can also serve as an important prior for many computer vision applications, e.g., object detection/recognition, scene categorization, and image retrieval. Examples in Fig. 1 show that Eiffel Tower has drastically different visual appearances in different weather conditions, which draws significant challenges on object/landmark recognition. Once weather properties can be estimated, an object detector/recognizer can adapt its parameters for different weathers, so that influence of visual variations can be reduced.

Although estimating weather properties from images poses many research potentials, related studies are just at their infant stages and emerging research ideas have not been well exchanged due to lack of common benchmark and baseline experimental studies. Our goal in this paper is to build a large-scale image dataset where images were captured by amateur photographers spanning across the Europe, and each is associated with rich weather information. To demonstrate that estimating weather properties from consumer photos is a doable computer vision research, in this work we particularly focus on: (1) How to collect a large-scale image collection associated with weather information and other useful metadata? (2) What explict/implicit knowledge is embedded by such cross-platform image data? (3) What kind of applications can be benefited by the estimated weather properties?

The rest of this paper is organized as follows. In Section III, we describe how to crawl weather information from a web-based weather platform, i.e., Weather Underground[1], based on an existing large-scale image collection that was collected from Flickr[2], i.e., the European City 1M (EC1M) dataset [5]. In Section IV, we will show interesting statistics derived from the collected dataset. Correlation between metadata/visual features and weather information will be demonstrated as the second contribution. Section V describe potential applications based on the proposed dataset, giving clues for future weather-related researches. Summary and future works are given in Section VI.

II. Related Works

Recently estimating weather property from visual content has been envisioned to give potential clues for computer vision applications. Narasimhan and Nayar [6] proposed one of the earliest works to study visual manifestations of different weather conditions. Chromatic effects are modeled for images

[1]http://www.wunderground.com/
[2]http://www.flickr.com

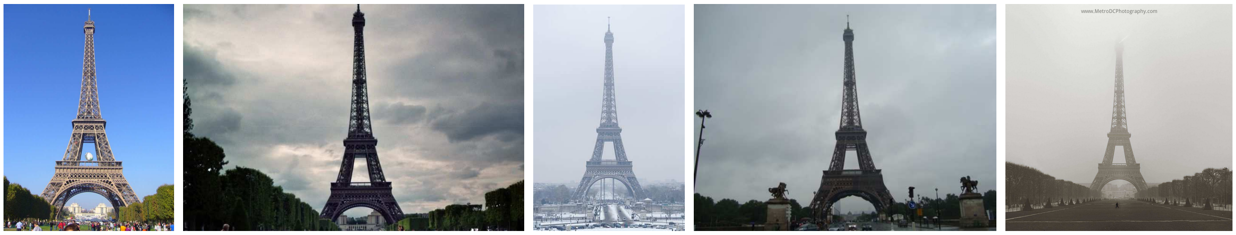


Fig. 1. Eiffel tower in different weathers. Left to right: sunny, cloudy, snowy, rainy, and foggy.

with fog or haze. They further presented the WILD database that consisted of registered and calibrated images of a fixed outdoor scene to facilitate related studies [7]. To enhance driver assistance systems on vehicles, Roser and Mossmann [8] constructed an SVM classifier based on contrast, intensity, sharpness, and color features to classify images captured by the camera mounted on vehicles into clear, light rain, and heavy rain weather conditions.

For years Jacobs and his colleagues have a series of studies on scene attributes based on an image dataset called the Archive of Many Outdoor Scene (AMOS) [9], in which images were captured by static webcams over a long period of time. In [9], they discovered scene variations incurred by weather conditions, human activity, and change of season at longer timescales. In [10], they augmented the AMOS dataset with automatic scene alignment and object labeling. Based on the augmented dataset, they proposed that webcams installed across the earth can be viewed as image sensors enabling us to understand weather patterns and variations. Later, the AMOS+C dataset [11] was proposed as the first large-scale image dataset associated with weather information. With the AMOS+C dataset, Jacobs and his colleagues explore the relationships between image appearance, sun position, and weather conditions [11].

Most recently, Laffont et al. [12] constructed regressors to estimate scene attributes, including lighting, weather, seasons and subjective impressions for images captured by webcams. Crowdsourcing techniques were used to label attributes for images selected from AMOS [9] and Webcam Clipart [13] datasets. In [14], Lu et al. proposed five weather features, i.e., sky, shadow, reflection, contrast, and haze, and proposed a collaborative learning framework to classify images into sunny or cloudy. A weather image dataset of moderate size (10K images) was collected from Flickr and the SUN dataset [15] for evaluation.

III. Building the Img2Weather Dataset

A. Cross-Platform Data Association

We need a large-scale image collection associated with heterogenous metadata to support rich image-weather association studies. In this work, we collect weather properties for each image from the Weather Underground website. Considering the most common potential applications, we mainly target the following weather properties:

- Five weather types: sunny, cloudy[3], snowy, rainy, and foggy.
- Temperature: in terms of centigrade, generally from $-25°$C to $45°$C.
- Humidity: from 0% to 100%.

According to our knowledge and availability of data, information related to the aforementioned weather properties includes, but not limited to:

- Taken time and taken location: Taken time indicates what season an image was taken, which is a factor highly correlated to an image's weather properties because the climate periodically changes. Taken location is also very important because weather is obviously a status limited to a locality.
- Textual annotation related to an image, such as tags, description, and image title: Text in these fields may implicitly or explicitly indicate weather properties, such as "hot", "cold", and "ski".
- Elevation: Temperatures at places with the same latitude would be significantly different because of higher elevation generally yielding lower temperature.

To quickly build a convincing dataset, we crawl weather-related information based on an existing large-scale image collection, i.e., the European City 1 Million (EC1M) dataset [5], which has been widely used in image clustering and retrieval. Based on the URL and photo ID available in EC1M, we adopt the Flickr API to obtain the image itself, and its associated metadata such as taken time, taken location, and tags. Based on taken location (in the representation of latitude and longitude), the corresponding elevation information (in the representation of meters) is acquired through the Google Maps API. Figure 2 is the framework of our web crawler. Table I shows the metadata collected from multiple platforms. Note that we totally collect more than twenty-eight properties, and list only a few of them in this table. In this work, we will not utilize all of these properties in building the estimation model. Readers are referred to our publicly available dataset for more details, and are welcome to discover usefulness of various properties in weather estimation in addition to the ones we use.

Based on longitude and latitude of an image, we utilize the Weather Underground API to retrieve more than thirty weather

[3]Note that we can collect a variety of cloudy conditions from the website, e.g., most cloudy and partially cloudy, but we roughly view all of them as cloudy.

TABLE I
TEXTUAL PROPERTIES AND THE CORRESPONDING MEANINGS OF COLLECTED METADATA, WHICH ARE OBTAINED FROM FLICKR AND GOOGLE MAPS*.

Property	*Meaning*
ID	Photo ID on Flickr
Owner	Owner of this photo
Dates	Date of image taken
URL	Associated URL
Title	Photo title
Comments	Number of comments
Tags	Associated tags
Location	Latitude and longitude
Views	Number of views
Visibility	Public or only shard with friends
Description	Textual description related to this photo
Elevation*	Associated elevation

properties, while Table II shows a subset of these properties. For an image captured at time t and located at longitude x and latitude y, we find the temporally closest weather record captured by the spatially closest meteorological station. If the spatial distance between this station and the image is less than five kilometers, and the temporal distance between the weather record and the taken time is less than two hours, the retrieved weather properties are used to "label" this image. Main properties to be estimated in this paper are weather types, temperature, and humidity, while other properties are left for future study.

Weather information on the Weather Underground website is from 60,000+ weather stations. With innovative forecast models and cross verification, it provides unrivaled amount of local neighborhood weather data. Figure 3 shows the cumulative distribution of distances from our collected images to their closest meteorological stations. For about 80% of images, the distance from them to the closest stations is less than four kilometers, which means that the retrieved weather information, if available, is quite accurate.

The advantages of using the EC1M dataset as the basis to collect cross-platform data association is worthy describing as follows. First, based on available photo ID and URL, we are able to quickly build a large-scale dataset associated with heterogeneous metadata. Second, photos in the EC1M dataset are mainly from big European cities, where meteorological stations are densely set up so that weather records are relatively richer and more accurate. Third, because the EC1M dataset was originally designed for landmark retrieval, with landmark information and the retrieved weather properties, researchers may be able to discover some implicit correlation between weather and landmarks, e.g., some place is more popular in winter if it is snowing.

B. Data Filtering

The EC1M dataset consists of 1,037,574 geo-tagged photos captured in 22 European cities. By excluding images with broken links and without corresponding weather properties, we totally collect 652,212 images from Flickr. A photo is said to have the corresponding weather properties if we can find a

TABLE II
WEATHER PROPERTIES OBTAINED FROM THE WEATHER UNDERGROUND WEB SITE.

Property	*Meaning*
type	Weather types: clear (sunny), cloudy, snowy, rainy, foggy
hum	Humidity
date	Local time of the weather record
utcdate	Coordinated universal time
tempm	Temperature in terms of Centigrade
tempi	Temperature in terms of Fahrenheit
dewptm	Dew point temperature in terms of centigrade[a]
dewpti	Dew point temperature in terms of Fahrenheit
wspdm	Wind speed kph
wspdi	Wind speed mph
wgustm	Wind gust kph
wgusti	Wind gust mph
wdird	Wind direction in degrees
wdire	Wind direction description
vism	Visibility in km
wismi	Visibility in miles
pressurem	Pressure in mBar
pressurei	Pressure in inHg
windchillm	Wind chill in terms of Centigrade[b]
windchilli	Wind chill in terms of Fahrenheit
heatindexm	Heat index in terms of Centigrade[c]
heatindexi	Heat index in terms of Fahrenheit
precipm	Precipitation in mm
precipi	Precipitation in inches

[a] http://apollo.lsc.vsc.edu/classes/idm3020/tut_folder/nick_tutorial/
[b] http://www.nws.noaa.gov/om/winter/windchill.shtml
[c] http://en.wikipedia.org/wiki/Heat_index

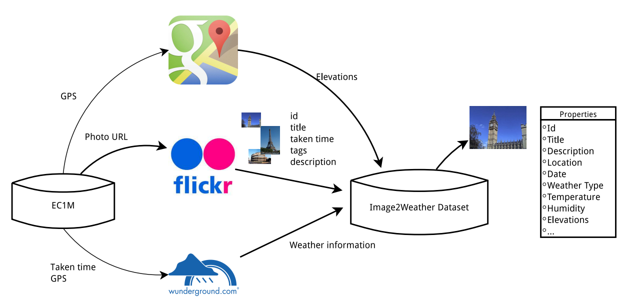


Fig. 2. The framework of our web crawler associating images with heterogeneous metadata (weather, tags, elevation).

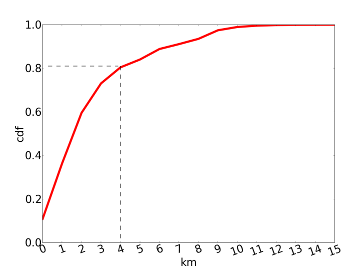


Fig. 3. Cumulative distribution function of distance between images and nearest weather stations.

weather record that is temporally apart from the photo's taken time within two hours, and is spatially apart from the photo's taken position within 4 kilometers.

For the sake of weather estimation, we focus on photos captured outdoors and within a photo the sky region occupies more than ten percent of the whole photo. To filter out photos captured indoors, we extract CNN (convolutional neural network) features based on the MatConvNet [16] toolbox as image representation, and accordingly construct a support vector machine (SVM) classifier to achieve indoor-outdoor classification. We collected totally 23,900 indoor photos and 17,906 outdoor photos from [17], the SUN database [15], and Flickr for classifier construction and evaluation. The pre-trained model in MatConvNet has five convolutional layers and three fully-connected layers. In this work, we take output of the seventh layer to be 4096-dimensional CNN features. Ninety percent of indoor and outdoor photos were randomly selected as the training data, and the remaining are for testing. According to our experiments, this classifier achieves more than 98% accuracy and facilitates us to largely eliminate indoor photos.

To detect sky in photos, we adopt the method proposed in [14] and classify each pixel into sky or non-sky. In addition to being used in data filtering, sky is also the region where several important visual features are extracted to build the weather estimation model (described in Section V).

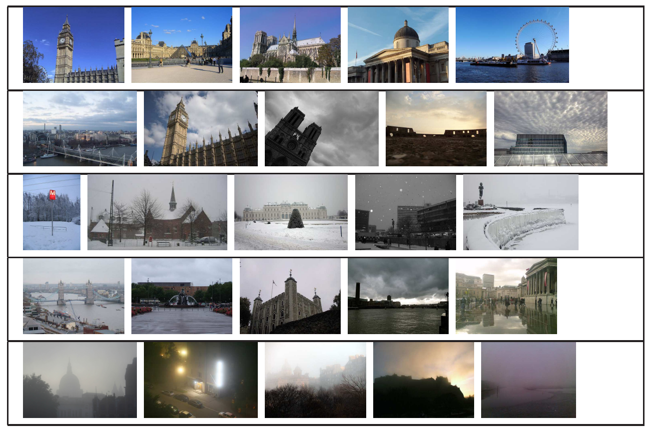
Table III shows statistics of the Image2Weather dataset after different stages of data filtering (top half) and numbers of photos in five different weather types. Note that the final dataset (D^*) consists of totally 25x,xxx images, which is much fewer than the number of images we originally collected (800,371 images). This is because we largely eliminate indoor images as well as outdoor images with the sky region no larger than 10% of the whole image. Overall, geographically the collected images span from 9.25 degrees west longitude to 30.4 degrees east longitude, and from 35 degrees north latitude to 62.21 degrees north latitude (covering most part of the Europe). The range of temperature is from $-25°$C to $45°$C, and the range of humidity is from 4% to 67%. From this table we can clearly see that numbers of images in different weathers are imbalanced, which reflects that people tend to travel and take photos in fine-weather (sunny or cloudy) days. Table IV shows images randomly sampled from the collected dataset, with five samples for each weather type. From these samples we can realize the challenge of weather type estimation due to significant visual variations. It is especially difficult to distinguish cloudy images from rainy images.

Fig. 4(a) and Fig. 4(c) respectively show mean/standard deviation of temperature and humidity in different weathers. As we expect, the lowest temperature happens on snowy days, whereas the highest temperature happens on sunny days. Snowy, rainy, and foggy days have higher humidity. Fig. 4(b) shows a temperature distribution across different months. Like the distribution often seen in a travel guide book, higher temperature happens in summer. Fig. 4(d) shows that humidity is higher from October to March in the next year, which also

TABLE III
STATISTICS OF THE IMAGE2WEATHER DATASET AFTER DATA FILTERING, AND THE NUMBER OF PHOTOS IN FIVE DIFFERENT WEATHERS IN THE FINAL DATASET.

D_1 = {Photos in EC1M}	1,037,574
$D_2 = D_1 \bigcap$ {Photos without broken links}	800,371
$D_3 = D_2 \bigcap$ {Photos with weather info.}	669,113
$D_4 = D_3 \bigcap$ {Outdoor photos}	293,071
$D^* = D_4 \bigcap$ {Photos with large sky}	25x,xxx
Number of sunny images	164,065
Number of cloudy images	72,405
Number of snowy images	2,190
Number of rainy images	14,957
Number of foggy images	2,220
Total	255,837

TABLE IV
FIVE RANDOM SAMPLES FOR EACH WEATHER TYPE. FROM TOP TO BOTTOM: SUNNY, CLOUDY, SNOWY, RAINY, AND FOGGY.

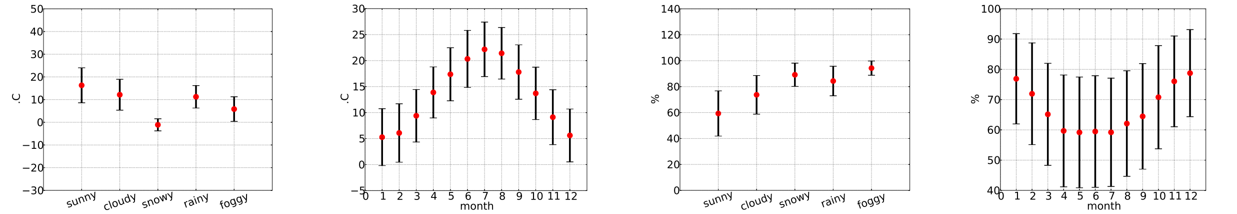


matches with our impression on Europe's winter and spring. These distributions show that characteristics of the collected images are quite typical.

Table V compares the Image2Weather dataset with previous ones in terms of geographical information, weather information, and fixed/dynamic viewpoints. The Weather and Illumination Database (WILD) [7] contains images captured from static viewpoints. The Archive of Many Outdoor Scenes (AMOS) dataset [9] is a large-scale outdoor image dataset coming from static webcams but without clear weather metadata. The Archive of Many Outdoor Scenes with Additional Context (AMOS+C) dataset [11] consists of a subset of the AMOS dataset [9] and associated weather data coming from a variety of sources. The dataset in [14] mainly contains images captured on sunny or cloudy days, and contains totally 10,000 images captured from dynamic viewpoints. Comparing with these datasets, the Image2Weather dataset consists of large-scale dynamic viewpoints images, richer weather information, and textual metadata collected from multiple platforms.

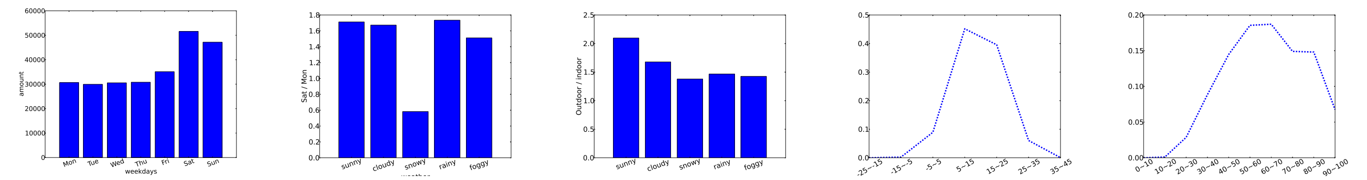
IV. ANALYSIS OF IMAGE2WEATHER

Based on the collected images, we first discuss the relationship between weather types and photo taking behavior. From the perspective of building weather estimation models from visual features, we then investigate how various features



(a) Mean and standard deviation of temperature in different weathers. (b) Mean and standard deviation of temperature in different months. (c) Mean and standard deviation of humidity in different weathers. (d) Mean and standard deviation of humidity in different months.

Fig. 4. Statistics showing the relationships between temperature/humidity and weathers, and between temperature/humidity and time.



(a) Numbers of images on different days. (b) The ratios of the number of images on Saturday to that on Monday. (c) The ratios of the number of images taken outdoors to indoors. (d) The ratios of the number of images within different temperature ranges. (e) The ratios of the number of images within different humidity ranges.

Fig. 5. Numbers of images on different days, different environments, in different weathers.

TABLE V
COMPARISON OF DIFFERENT DATASETS.

Dataset	*Geo.*	*Weather*	*Viewpoints*	*#images*
WILD [7]	yes	yes	static	3K
AMOS [9]	some	no	static	17M
AMOS+C [11]	yes	yes	static	3.5K
[14]	no	yes	dynamic	10K
Image2Weather	yes	yes	dynamic	255K

correlate with weather types, temperature, and humidity. Features used in this work include photo taken time, RGB color histogram, Gabor wavelet texture [19], intensity histogram, cloud features [20], local binary pattern (LBP) [21], contrast features, and haze features [14].

Relationship between weather type and photo taking behavior. The following statistics are obtained based on all images with weather information (669,113 images). Fig. 5(a) shows numbers of photos taken on different days. It is not surprising that photos taken on weekends are more than that taken in weekdays. Fig. 5(b) shows the ratio the number of images on Saturday to that on Monday, in different weathers. We can clearly see that the ratios are larger on sunny, cloudy, and rainy days, indicating in such weathers people tend to travel more and take more photos on weekends. On the other hand, when it is snowy, the number of photos taken on weekend is similar to that on weekdays. Fig. 5(c) shows the ratio of the number of images taken outdoors to indoors, in different weathers. As we expect, more photos were taken on sunny and cloudy days. The number of photos taken outdoors is only 80% of that taken indoors when it is snowy. Figure 5(d) shows numbers of photos vs. temperature ranges. It can be seen that more photos were taken when the temperature ranges from $5°$C to $25°$C. Figure 5(e) shows numbers of photos in different humidity ranges.

TABLE VI
RATIOS OF THE NUMBER OF SUNNY OR CLOUDY PHOTOS TO TOTAL NUMBER OF PHOTOS; AND RATIOS OF THE NUMBER OF VIEWS IN SUNNY OR CLOUDY PHOTOS TO TOTAL NUMBER OF VIEWS.

Landmark	*Ratio of Photos*	*Ratio of Views*
Colosseum	Sunny: 0.79	Sunny: 0.77
	Cloudy: 0.17	Cloudy: 0.16
Big Ben	Sunny: 0.64	Sunny: 0.67
	Cloudy: 0.28	Cloudy: 0.25
Eiffel Tower	Sunny: 0.49	Sunny: 0.44
	Cloudy: 0.44	Cloudy: 0.51
Notre Dame	Sunny: 0.50	Sunny: 0.52
	Cloudy: 0.41	Cloudy: 0.41
London Eye	Sunny: 0.64	Sunny: 0.67
	Cloudy: 0.27	Cloudy: 0.25

Table VI shows "the ratios of numbers of photos taken on sunny (cloudy) days to that taken on all days", as well as "the ratios of numbers of views in sunny (cloudy) photos to the total number of views", at several famous landmarks. Most of them have similar patterns, i.e, there are more photos and views on sunny days. For Eiffel Tower, the difference between sunny photos and cloudy photos is not as apparent as other landmarks. Interestingly, we can observe that photos of Eiffel Tower captured on cloudy days attract more views. This discovery may inspire new research direction, e.g., some place is more popular in specific weather conditions.

The relationship between time distance and weather properties. Considering two photos that were taken on the same day. It is expected that weather properties of these two photos differ more if their were taken at larger temporal distance, e.g., one was taken in the early morning and another one taken in the late afternoon. However, when we consider photos at a larger scale, e.g., one year, periodicity of climate change may play an important role in measuring weather property difference. For example, temperature of a photo taken at noon of someday in March may be similar to that of a photo taken at noon of someday in September, because temperature changes in spring and in fall are similar.

We especially care the month and the hour when a photo was taken, because month information embeds which season this photo was taken, and hour information is correlated with sunlight. Let us consider two photos taken at (m_1, h_1) and (m_2, h_2), respectively, here m_1, m_2, h_1, and h_2 are months and hours of the taken time of two photos. To investigate the relationship between time distance and weather properties, in the meantime to consider periodicity of climate change, we collect average temperature of every month from the weather forecast website. These data points are then fit by a polynomial curve f. The curve f acts as a function that transforms month information m into the value $\hat{m} = f(m)$, which indicates the estimated average temperature of the month m. Similarly, we can also fit average temperature of every hour and fit them with a curve (function) g, which then transforms hour information h into the value $\hat{h} = g(h)$. The time distance between the considered two photos is thus calculated by $\sqrt{w_1(\hat{m}_1 - \hat{m}_2)^2 + w_2(\hat{h}_1 - \hat{h}_2)^2}$. The weight $w_1 = 10w_2$ is designed to emphasize the distance between months.

Fig. 6(a) shows probabilities of sharing weather types vs. time distances between photo pairs. The x-axis denotes the time distance between photo pairs calculated by the equation mentioned above, and the y-axis denotes the probability of sharing the same weather type. For example, the red triangle in this figure shows that the probability of two photos belonging to the same weather type is 0.5, if their time distance is 2. From this figure, we see that the probability of sharing the same wether type decreases as the time distance between photos increases. Fig. 6(e) is a heat map showing the relationship between temperature distance and time distances. The x-axis denotes the time distances between photo pairs, and the y-axis denotes the temperature distances between photo pairs. For example, the white circle in this figure shows that, when the time distance between a photo pair is 1 (x-axis), the probability of their temperature distance ranges from 0 to 1 degree centigrade (y-axis) is around 0.225. The white triangle, on the other hand, shows that, when the time distance between a photo pair is 5 (x-axis), the probability of their temperature distance ranges from 0 to 1 degree centigrade (y-axis) is around 0.05. When the taken time of two photos is close, the probability of their temperature distance less than two degrees centigrade is much higher than other cases. Similarly, Fig. 6(i) is the heat map showing the probability of humidity distance within a range versus time distance between photos. A trend similar to Fig. 6(e) can be seen. Particularly when the time distance between two photos is small, the probability of humidity distance less than 5% is much higher than other cases.

The relationships between visual feature distances and weather properties. Fig. 6(b) shows the probability of sharing weather type versus photo pairs' RGB color histogram distances (measured by Euclidean distance). We can see smaller distance between color distributions indicating higher probability of sharing weather type. On the other hand, from the dynamic range of probability we see this effect is relatively moderate and noisy, comparing with the effect shown in Fig. 6(a). Fig. 6(f) is the heat map showing the relationship between color histogram distance (x-axis) and temperature distance (y-axis) within a range. We see that, if color histogram distance is less than 0.3, the probability of temperature distance less than one degree centigrade is much higher than other cases. This confirms that color distribution distance would be a good feature for us to estimate temperature. Fig. 6(j) also shows the characteristic on estimating humidity.

What is the relationship between other visual feature distances and weather properties? Generally, the trends derived from other visual features are similar to that from color distribution, while the strength would be different. Comparing the heat maps in Fig. 6(g) and Fig. 6(k) with Fig. 6(f) and Fig. 6(j), respectively, we see that texture features would be more reliable to estimate temperature and humidity because the patterns are more concentrated. On the contrary, Fig. 6(l) shows that intensity distance is a rather weaker feature to estimate humidity.

The same analysis is also done for describing the relationship between other feature distances and weather properties. We skip detailed illustration because relationships similar to color features and texture features can be observed. The influences of different features on weather properties are different and complex. In Section V, we will construct weather estimation models that automatically adopt features with different extents learned from training data.

V. Applications of Image2Weather

A. Weather Type Classification

Based on Image2Weather dataset, we construct a random forest classifier [22] to estimate weather type for a given image. A random forest classifier is composed of a number of decision trees, and each decision tree is a simple and weak classifier. By combining results of a large number of weak classifiers, a robust classification result can be obtained. In this work, totally 100 decision trees are constructed to constitute the random forest. To construct this random forest classifier, for each weather type we randomly sample 1,100 images from the collected Image2Weather dataset. The random-split scheme is used for training and testing. That is, for each run 1,000 images are randomly selected from each weather type for training, and the remaining 100 images are for testing. We conduct ten runs of training and testing in this application.

Table VII shows the confusion matrix of weather type classification, where columns show truth types and rows show estimated types. Encouraging classification results (around or higher than 70%) are obtained for the weather types of sunny, cloudy, and snowy. These results show that estimating weather types from single images is promising, even based on simple visual features and time information. Much more accurate

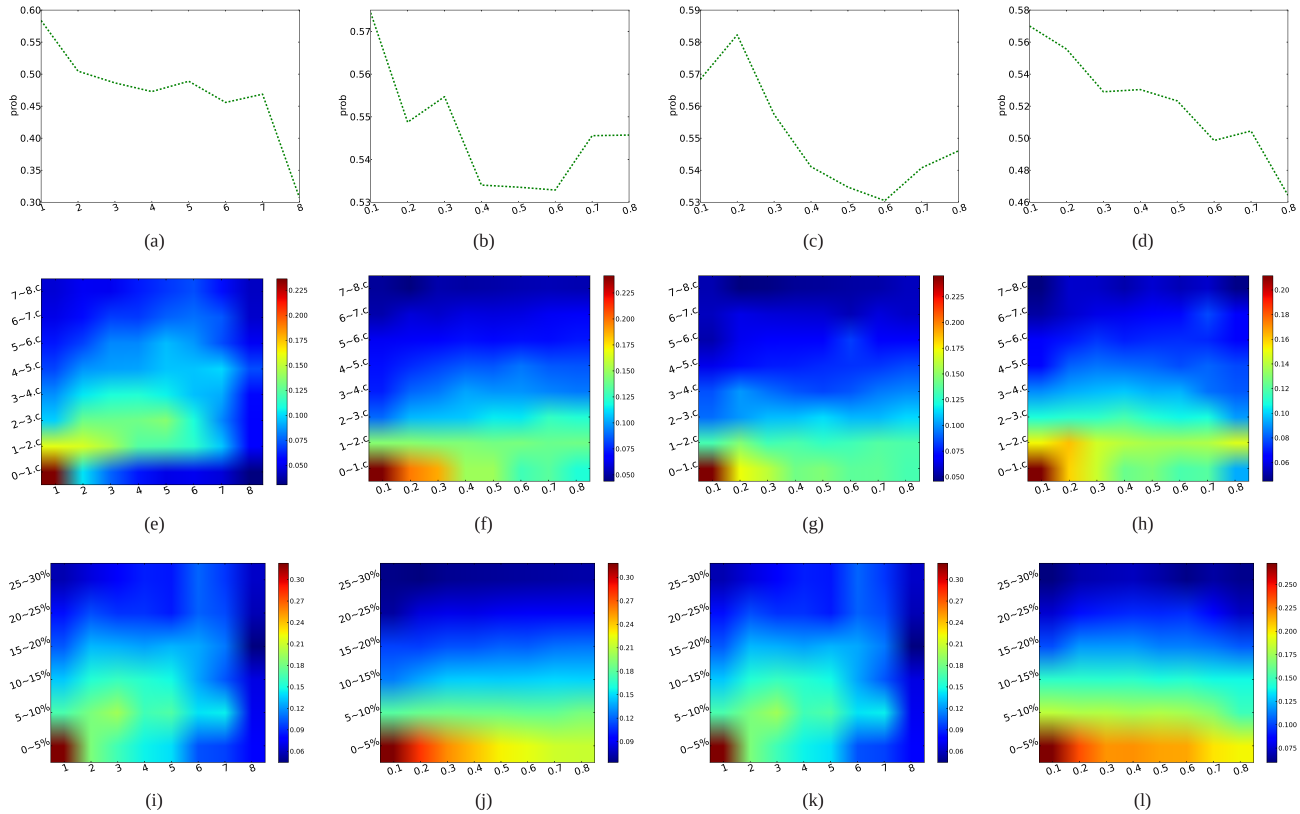


Fig. 6. Relationships between various properties and weather properties. (a)–(d) The prob. of sharing the same weather type vs. time/color/texture/intensity distances. (e)–(h) The prob. of temperature distance within a range vs. time/color/texture/intensity differences between photo pairs. (i)–(l) The prob. of humidity distance within a range vs. time/color/texture/intensity differences between photo pairs. (Better viewed in color)

results than random guess, i.e., 0.20, can be obtained by the proposed method, even for the rainy and foggy images that are relatively difficult to be classified. The relatively worse performance for rainy and foggy images is not beyond our expectation, and may attribute to the following factors: noises in data, user's photo taking behavior, and weakness of visual features. First, information of the meteorological station closest to a photo is used to be its ground truth. Sometimes weather conditions differ in two places even they are apart from each other by five kilometers. Moreover, it is sometimes difficult for people to distinguish rainy photos from cloudy photos. Second, people tend to take photos with less rain even it is raining. We seldom see a photo taken in rainy days consist of many raindrops. In most cases, only gloomy sky can be seen in such photos. Third, when it is foggy, features like texture, LBP, and contrast may not well describe image content due to blur appearance.

B. *Temperature and Humidity Estimation*

We formulate the temperature estimation task as a regression problem, and use random forest regressors to estimate temperature. Given the training set, a random forest consisting of a number of decision trees is constructed. We construct a random forest consisting of 100 decision trees, based on the eight types of features mentioned above. Given an image, we traverse each decision tree based on extracted features to the leaf, and calculate mean temperature of training images at this leaf as the estimated temperature. The 100 estimated temperatures from 100 decision trees are averaged to be the final estimation value. Similarly, the humidity estimation task can also be formulated as a regression problem and solved by random forest regressors.

Similar to weather type classification, we perform temper-

TABLE VII
THE CONFUSION MATRIX OF WEATHER TYPE CLASSIFICATION BASED ON THE RANDOM FOREST CLASSIFIER.

	sunny	cloudy	snowy	rainy	foggy
sunny	0.83	0.07	0.03	0.03	0.05
cloudy	0.05	0.69	0.05	0.18	0.04
snowy	0.05	0.06	0.68	0.10	0.13
rainy	0.04	0.22	0.10	0.52	0.14
foggy	0.14	0.10	0.14	0.17	0.47

TABLE VIII
THE CONFUSION MATRIX OF WEATHER TYPE CLASSIFICATION BASED ON THE KNN CLASSIFIER.

	sunny	cloudy	snowy	rainy	foggy
sunny	0.80	0.10	0.04	0.04	0.03
cloudy	0.04	0.73	0.06	0.16	0.02
snowy	0.05	0.09	0.66	0.12	0.08
rainy	0.03	0.27	0.19	0.41	0.09
foggy	0.14	0.12	0.21	0.15	0.38

ature estimation for 100 runs. At each run, 1,000 images are randomly selected as the training data, and the remaining 100 images are for testing. The average Pearson correlation and Spearman correlation after 100 runs are 0.85 and 0.84, respectively. The estimation results are highly correlated with the ground truth, indicating that estimating temperature from single images is an encouraging research direction. The average difference between estimated temperature and the ground truth is around $3.48°$C.

For humidity estimation, after 100 runs, the average Pearson correlation and Spearman correlation are 0.74 and 0.64, respectively. The estimation results are also highly correlated with the ground truth. The average difference between estimated humidity and ground truths is around 9.58%. Generally, estimating humidity is relatively less reliable in our work.

Figure 7 shows some samples of weather type classification, temperature estimation, and humidity estimation. We see that very promising results can be obtained if a photo was well taken to include the sky region.

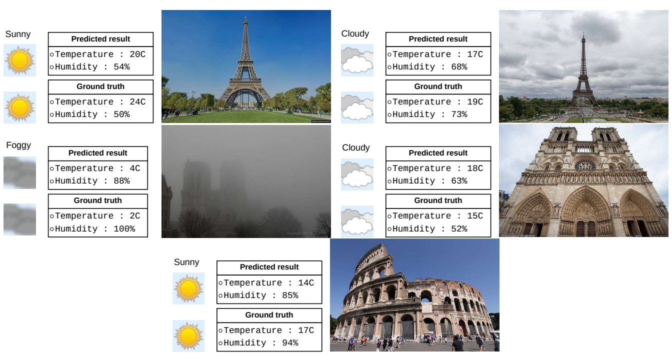


Fig. 7. Examples of weather properties estimation. Photos at the top row are sunny and cloudy Eiffel Tower in Paris, respectively. Photos at the second row are foggy and cloudy Notre Dame in Paris, respectively. The photo at the last row is sunny Colosseum in Rome.

VI. Conclusion

We have presented a large-scale image dataset where images were captured in all around the Europe and from various perspectives, and are associated with rich weather information obtained from a weather forecast website. This information-rich dataset thus brings many research potentials in the computer vision society. In this paper, we explore photo taking behaviors from the Image2Weather dataset, and investigate the relationship between visual feature differences and weather types. These studies further facilitate the development of weather estimation models. In the future, more interesting characteristics considering various weather properties are to be explored, and advanced weather estimation models are to be built based on the dataset.

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