

# What makes a great poster?

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RSS Conference Co-Chair 2018; IBS CNC Conference Chair 2017  
(but have only ever made one poster myself)

12 August 2021

What does success look like?

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- ▶ best poster prize

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- ▶ best poster prize
- ▶ one great conversation
- ▶ several good conversations

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- ▶ best poster prize
- ▶ one great conversation
- ▶ several good conversations
- ▶ getting help with a problem
- ▶ getting people to read your paper

# What does success look like?

- ▶ best poster prize
- ▶ one great conversation
- ▶ several good conversations
- ▶ getting help with a problem
- ▶ getting people to read your paper
- ▶ ...easy to make? easy to print? easy to transport?

success = best poster prize?

visuals trump all else

- ▶ less is **much** more
- ▶ self-explanatory content  
(because judging is often done outside poster sessions)

# success = best poster prize?

## Haiti: Cholera figures (Jan-Feb 2015)



The total number of cholera cases decreased significantly in 2014. However, delayed rains, compounded by deficiencies in the Port-au-Prince water-supply network, including illegal tapping and a deficient alert and coordination system, resulted in a drastic increase in the number of cases and deaths in the last quarter of the year. This worrying trend continues in 2015 and highlights the need to increase cholera contingency measures ahead of the upcoming rainy season (April - May).



### CHOLERA CASES

#### JAN-FEB 2015



#### OCT 2010-FEB 2015



### WHERE (JAN-FEB 2015)



### FUNDING

Cholera response remains underfunded. This will likely be an issue in the second half of 2015, as some donors no longer consider cholera to be an emergency. OCHA and OCHA-managed pooled funds remain the only sources of humanitarian funding.

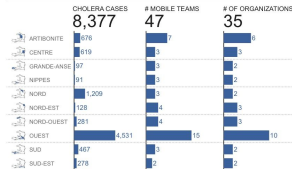
**NATIONAL PLAN (2013-2022)**  
**\$2.2B**



**UN SUPPORT PLAN (2014-2016)**  
**\$72M**



### RESPONSE (JAN-FEB 2015)



#### WHY DOES CHOLERA STILL PERSIST?

- Weak water and sanitation infrastructure
- Lack of access to quality medical care
- Deficiencies in the alert and coordination system
- Deficiencies in the distribution of the water-supply network

The boundaries and names shown and the designations used on this map do not imply official endorsement or acceptance by the United Nations.

Creation date: 7 Apr 2015. Sources: Accuweather, MSF, OPSOMS, INRCEP. Feedback: ocha.haiti@un.org | www.ocha.org | www.reliefweb.int



success = one great conversation?

(some) detail needed

- ▶ links to related work  
(especially if others in the field may be at the meeting!)
- ▶ **but** what's the **big** idea?

# success = one great conversation?

## Expression Invariant Face Recognition with a 3DMM

Brian Amberg  
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Research  
UNIBAS

### Contribution

We introduce a method for expression invariant face recognition. A generative 3D Morphable Model (3DMM) is used to separate identity and expression components. The expression removal results in greatly increased recognition performance, even on difficult datasets, without a decrease in performance on expression-free datasets. It is applicable to any kind of input data, and was evaluated here on textureless single scans.

### Model

The Model was learnt from 175 subjects. We used one neutral expression scan per identity and 30 expression scans of a subset of the subjects.

The identity model is a linear model build from the neutral scans.

$$f = p + M_n \alpha_n \quad (1)$$

For each of the 30 expression scans, we calculated an expression vector as the difference between the expression scan and the corresponding neutral scan of that subject. This data as a study made-constant, if we regard the neutral expression as the natural mode of expression data. From these offset vectors an additional expression matrix  $M$  was calculated, such that the complete linear Model is

$$f = p + M_n \alpha_n + M \alpha_e \quad (2)$$

The assumption here is, that the face and expression space are linearly independent, such that each face is represented by a unique set of coefficients.

### Fitting

A robust nonrigid ICP method was used to fit the model to the data. Robustness was achieved by iteratively reweighting the correspondences and using a hard-compatibility test for the closest points.

Fitting was initialized by a simple nose detector and passeded fully automatic.

### Distance Measure

The Mahalanobis angle between the identity coefficients  $\alpha_n$  was used for classification.

### Open Questions

While face-expression and identity space are linearly independent, there is some expression left in the identity model. This is because a "neutral" face is interpreted differently by the subjects. We investigate the possibility to build an identity-expression separated model without using the data labeling, based on a measure of independence.

### References

- [1] B. Amberg, S. Romdhani, J. Tomasi. "Optimal step size rigid ICP: Algorithm for surface registration." In: CVPR 2007.
- [2] B. Amberg, S. Romdhani, J. Tomasi. "Expression Invariant Face Recognition with a 3D Morphable Model." In: MICCAI 2007.

### Expression Neutralization



Expression neutralization for two scans of the same individual. The robust fitting gives a good estimate (b) of the true face surface given the noisy measurement (a). It fills in holes and removes artifacts using prior knowledge from the face model. The pose and expression neutralized faces (c) are used for face recognition.

### Robustness

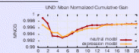
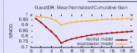


The reconstruction (b) is robust against scans (a) with artifacts, noise, and holes. This is achieved by a robust iteratively reweighted ICP algorithm and outlier rejection based on angle comparison between corresponding points.

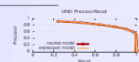
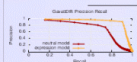
### Results

The method was evaluated on the ConFD-B expression dataset which contains 427 Scans, with 3 neutral scans and 4 expression scans per ID. To test the impact of expression invariance on recognition

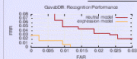
we also used the UNED dataset from the Face Recognition Grand Challenge Test, which contains 953 neutral scans with one to eight scans per subject.



Expression neutralization improves results on the expression dataset without decreasing the accuracy on the neutral testset. Plot (a) is the ratio of correct answers to the number of possible correct answers.



Plot (a) are precision and recall for different retrieval depths. The lower precision of the UNED database is due to the fact that some queries have no correct answers.



Impostor detection is reliable, as the minimum distance to a match is smaller than the minimum distance to a nonmatch.

### Funding

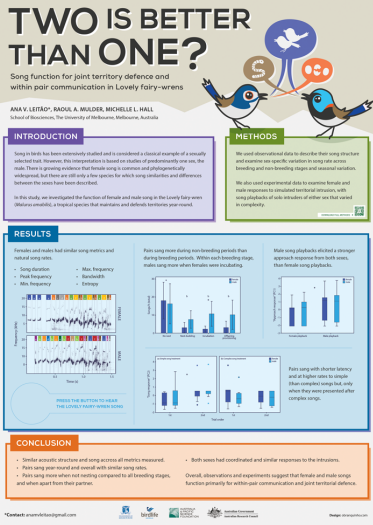
This research was supported in part by SNSF grant 31-138599 through the European Research Council.

success = several good conversations?

draw people in with wide applicability

- ▶ e.g. like sports? read this poster!
- ▶ be controversial or surprising  
(e.g. do **you** believe in the placebo effect?)

# success = several good conversations?



success = getting help with a problem?

## ask questions

- ▶ e.g. can you complete this proof that Bayes is uniformly optimal?
- ▶ e.g. I can't explain the correlation between sandy beaches and sandwich consumption — can you?

success = getting help with a problem?

Robert Verbaagh    Martin Verhees    Erik Maris    Ad Van de Walle

# OPEN CORPUS ADAPTIVE NAVIGATION

**TRY  
IT  
LIVE  
HERE  
NOW**

insert content  
for adaptation

Links to a user's preferred actions are inserted automatically with client-side Semantic Web technology.

```
graph LR; Client[Client] -- request --> Publisher[Publisher]; Publisher -- hypermedia --> Client; Adapter[Adapter] -- affordance --> Client; Adapter -.- service description -.- Provider[Provider];
```

An adapter at the client side adds distributed affordance to the hypermedia representation created by the server, based on the semantic annotations contained therein. The actions are instantiated from service descriptions.

For a platform demo, visit [distributedaffordance.org](http://distributedaffordance.org)

MULTIMEDIA  
iMinds  
UNIVERSITY OF  
GENT

success = getting people to read your paper?

tease, but don't reveal too much!

- ▶ simplify (#betterposter)
- ▶ point to the paper for the details people need

success = getting people to read your paper?

## Title

Authors

### Intro



### Methods

1. [bar]
2. [bar]
3. [bar]
4. [bar]

### Results



### Discussion

More research is needed, but...

- [bar]
- [bar]
- [bar]



**Main finding** goes here,  
translated into **plain english**.  
**Emphasize** the important  
words.



Take a picture to  
download the full paper

## Extra Tables & Figures





FIN

# Ignorability

and unbalanced longitudinal data

DANIEL FAREWELL

CHAO HUANG

VANESSA DIDELEZ

## No such thing\* as missing data, authors claim

Marked point processes offer clearer perspective

Most treatments of dropout within longitudinal studies rely on a missing data framework: usually, that of Rubin (1976). This implicitly presumes, however, that the missing data actually exist, and important notions such as 'ignorability' and 'missing at random' are based on their assumed properties.

But how are we to determine whether such assumptions are reasonable? Difficulties arise because (for instance)



it is not clear what exactly is meant by 'the customer satisfaction score that would have been recorded, had this individual not died, but instead decided to attend their scheduled dental checkup'.

So can we define a condition equivalent to ignorability but without appealing to missing data? We think so, with careful consideration of the causal relationship between the points and marks of a

marked point process. In a marked point process, we have the points (that is, the observation times)

$$t = (t_1, t_2, t_3, \dots)$$

and the marks (the observations)

$$y = (y_1, y_2, y_3, \dots)$$

and that's basically it. Once observations stop, it helps to think of the 'observation times' as infinite, with associated irrelevant marks. But there's no 'underlying longitudinal process'. No missing data.

Instead, formulate a causal model relating the points to the marks, and use it to write down the joint likelihood:

$$p(t, y)$$

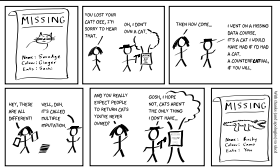
Ignorability then boils down to a simple question: are there parts of this joint likelihood that can be ignored?

### Here's a simple example

Suppose that the point process can depend on the values of previous marks. For instance, findings on medical checkups might be used to schedule subsequent checkup dates. Let's also assume that checkup findings are correlated, modelled using a random effect. Here's (part of) a causal DAG:



Use this to write out the joint likelihood of the points and the marks, and you'll get something like the expression on the right. Assuming no parameters in common, that first factor can be completely ignored, leaving just the familiar mixed model likelihood.



$$p(t, y) = \prod_j p(t_j | t_1, \dots, t_{j-1}, y_1, \dots, y_{j-1})$$

Look! It's the usual mixed effects model!

$$\times \prod_u p(u) \prod_j p(y_j | t_j, u)$$

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